Commodity Price Forecasting Using Deep Learning Techniques:

In the Case of Ethiopian Commodity Exchange (ECX)

Abera Geda Debela

A Thesis Submitted to the Department of Computer Science and Engineering

School of Electrical Engineering and Computing

Presented in partial fulfillment of the requirement for Degree of master's in Computer science and Engineering

Office of Graduate Studies

Adama Science and Technology University

September, 2022

Adama, Ethiopia

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Declaration

I hereby declare that this master thesis entitled "**Commodity Price forecasting using Deep learning Techniques: In the case of Ethiopian Commodity Exchange (ECX)**" is my original work. That is, it has not been submitted for the award of any academic degree, diploma, or certificate in any other university. All sources of materials that are used for this thesis have been duly acknowledged through citation.

Abera Geda Debela	______________________	_______________
Name of student	Signature	Date

Recommendation

I, the advisor of this thesis, hereby certify that I have read the revised version of the thesis entitled "**Commodity Price forecasting using Deep Learning Techniques: In the case of Ethiopian Commodity Exchange (ECX)**" prepared under my guidance by **Abera Geda** submitted in partial fulfillment of the requirements for the degree of masters of science in computer science and Engineering. Therefore, I recommend the submission of the revised version of the thesis to the department following the applicable procedures.

Bahiru Shifaw (Ph. D)	________________________	________________
Major Advisor/Supervisor	Signature	Date

Approval Page

I the advisor of the thesis entitled "**Commodity price forecasting using deep learning techniques: In the case of Ethiopian Commodity Exchange**" and developed by **Abera Geda,** hereby certify that the recommendation and suggestions made by the board of examiners are appropriately incorporated into the final version of the thesis.

Major Advisor	Signature	Date

We, the undersigned, members of the Board of Examiners of the thesis by **Abera Geda** have read and evaluated the thesis entitled "**Commodity price forecasting using deep learning techniques: In the case of Ethiopian Commodity Exchange**" and examined the candidate during the open defense. This is, therefore, to certify that the thesis is accepted for partial fulfillment of the requirement of the degree of Master of Science in Computer science and Engineering.

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Finally, approval and acceptance of the thesis is contingent upon submission of its final copy to the Office of Postgraduate Studies (OPGS) through the Department Graduate Council (DGC) and School Graduate Committee (SGC).

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Office of Postgraduate Studies, Dean	Signature	Date

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LIST OF ABBREVIATIONS

ANN	Artificial Neural Network
ARIM	Autoregressive Integrated Moving Average
Av	Average
BILSTM	Bidirectional long short-term memory
CART	Classification Regression Tree
CNN	Convolution Neural Network
Ch	Changes
CP	Close price
CC	Correlation Coefficient
CPU	Central Processing Unit
CSV	Comma Separated Value
D	Days
ECX	Ethiopian Commodity Exchange
GDP	Gross Domestic Product
GPU	Graphics Processing Unit
GRU	Gated Recurrent Units
H	High
IDE	Integrated Development Environment
KNN	K _Nearest Neighbor
L	Low

LSTM	Long Short-Term Memory
LSTnet	Long short-term network
MAPE	Mean Absolute Percentage Error
MAE	Mean Absolute Error
MSE	Mean Squared Error
Ph	production year
RMSE	Root Mean Squared Error
RNN	Recurrent Neural Network
SVR	Support Vector Regression
V	Volume
W	Weeks
XLSL	Excel Extension

ABSTRACT

One of the economic development plans of Ethiopia is to enhance the agricultural sector by creating an effective linkage between producer and commodity markets. ECX has been working on creating this effective linkage by providing market information related to commodity prices for producers and traders. But the fluctuation of commodity prices from month to month as well as year to year is the most challenging problem. These changes in commodity prices affects the gross domestic product (GDP) of Ethiopia. Another impact of commodity price fluctuations is on the farmer who produces the agricultural products. They sell their commodities at a low price due to less information about future market directions. This is due to no scientific way of forecasting the commodity price for long term in the future. People simply give their deductions regarding the future price of a commodity as it increases or decreases without using any systematic ways. So, there is importance of intelligent decision-making techniques that follow scientific methods to solve the forecasting problem. The goal of this study was to use the Deep Learning technique, which is a scientific method, to forecast the future prices of the top three export agricultural commodities: coffee, sesame, and green mung beans based on historical data collected from the Ethiopian commodity exchange (ECX). This raw data, collected from the Ethiopian commodity exchange, passes through many preprocessing steps to be usable by deep learning models. Among deep learning techniques, long short-term memory, gated recurrent unit, and bidirectional long short-term memory algorithms which perform well on historical time series datasets are implemented and the results obtained from each of them were compared after hyperparameter tuning. The outperform model was selected. Accordingly, long short-term memory (LSTM) was selected as the best model after being evaluated with regression model evaluation metrics like mean squared error (MSE), root means squared error (RMSE), and mean absolute error (MAE) with very low loss function and high accuracy. The accuracy obtained using LSTM was 99.93%. Therefore, the long-short term-based model was used to effectively forecast the future price of agricultural commodities like coffee, sesame, and green mung beans. Even if this model plays its role in forecasting the prices of the top three most exported agricultural commodities, we recommend extending this study by including factors that affect the prices of those commodities using new technology.

Keywords: Deep learning, Coffee, Sesame, Green mung beans, LSTM, GRU.

CHAPTER ONE

1 INTRODUCTION

This introductory part of the study is to provide the overview of the study, such as the background of the study, statement of the problem, motivation of the study, research question, the objective of the study, and significance of the study.

1.1 Background of the study

One of the Ethiopia's ten-year economic development plans focuses on the agricultural sector (Teddy Tefera, 2021). The development plan has laid out enhancing agricultural production and productivity as the main strategic pillars of the economy. Additionally, the Ethiopian government is committed to speeding up agricultural development as a way to lessen poverty and advance the country's economic transformation (Mellor & Dorosh, 2010). An agricultural commodity is one of the agricultural products which undergoes only a few preprocessing steps. It is a key input utilized as a raw material to create other services. In addition to being utilized for exports and as industrial inputs, agricultural commodities are sorts of crops that are widely produced in our country and used for domestic's consumption.

The economic development plan of the agricultural sector of the Ethiopian government is aimed to establish an effective linkage between agricultural producers(farmers) and commodity markets as well as the commercial value chain (Teddy Tefera, 2021). This effective linkage is carried out through the Ethiopian commodity exchange (ECX). It is the most effort to improve the efficiency of agricultural markets. The ECX was created to serve as a marketplace for buyers and sellers of grains, and coffee to plan effective and open market operations(Bizualem & Saron, 2018). It is a privately held firm that is jointly controlled by the Ethiopian government, exchange participants, and market actors. Ethiopian commodity has more than 450 legally registered buyers/exporters that are a member of the exchange with the license to bid for and export (Bizualem & Saron, 2018). There are two ways for Ethiopian goods to be exported to foreign markets: first, through the Ethiopian commodity exchange, and second, through a legally recognized cooperative union that can export goods directly to different nations throughout the world.

The Ethiopian commodity exchange is working on many types of commodities like coffee, sesame, Red Kidney Bean, White Pea Bean, Green Mung Bean, Chickpeas, Soybeans, wheat, maize, Pinto Bean, and white pigeon pea.

Ethiopian commodity exchange started in April 2008 (Gebisa, 2019). It is a new organization for Ethiopia and the first commodity exchange in Africa too. Its goal is to ensure the creation of a successful, cutting-edge trading system that safeguards the interests of buyers, sellers, and the general public ((Gebisa, 2019), and works on controlling agricultural commodities move from producers to consumers of commodities. Commodities have to go through one or more links in the industrial chain of production, acquisition, processing, storage, transportation, whole sales, and retail (Luyao Wang, 2020).

The establishment of ECX was instituted by proclamation no.550/2007. According to the proclamation, Ethiopia's commodity exchange can develop its own rules and regulations which are used to govern the operation under ECX (Gebisa, 2019). The rules developed by ECX, which are known as the rules of exchange, are used as a blueprint for other rules that govern membership, clearing, warehousing, trading, and settlements in the Ethiopian commodity exchange. The main vision of ECX is to transform the crawling economy of Ethiopia by making the best global commodity market of its choice by connecting all buyers and sellers in a reliable, efficient, and transparent market manner. It is the place where commodities that are collected from producers can be ready for sale and ready for export purposes. Due to increasing historical data as well as price fluctuations, machine learning techniques that have the intelligence to forecast the price of commodities in the future will have valuable benefits (Chen et al., 2021). To improve the advantage obtained from agriculture or to improve the quality of agricultural products, future price forecasting using machine learning plays a great role (Zhao, 2021). Ethiopian commodity exchange is working on most known commodities like coffee, which holds more than half of all exports. Sesame is the second most exported good. Soybeans, maize, red kidney bean, white pea bean, pinto bean, and green mung bean are the common goods used for exchange. Those commodities are produced by farmers, and they need a way to predict commodity prices to increase productivity (Gebisa, 2019).

Ethiopia is rich in agricultural resources and has a wide range of agro-ecological zones. Farmers harvest a variety of crops for food and as cash crops to earn money. The Crop production is the most important subsector, accounting for almost 60% of agricultural GDP and 80% of exports, according to the Agricultural and Food Security Ethiopia. Among the cash crops harvested in Ethiopia, commodities like coffee, sesame, and green mung beans are placed at the top (Eshetu & Mehare, 2020).

Coffee: Ethiopia is the major producer and consumer of coffee in the region and its coffee production has increased rapidly over the last three years, and with favorable growing circumstances, is expected to reach 7.62 million bags (457,200 MT) in 2021 and 2023. Domestic consumption accounts for 50–55 percent of Ethiopian coffee production. Ethiopia is the country in Africa that is leading in exporting coffee commodities to the international market. Coffee grows in different parts of Ethiopia and each of them is known by a different brand name in international markets. Coffee is one of the agricultural commodities Ethiopia exports and is placed at the top. It accounts for more than 70% of total export revenues (Gebisa, 2019), and it is the most important agricultural export crop, accounting for 20%-25% of foreign exchange revenues (ECFF, 2015). Coffee is wrapped and classed according to cup profile and quality upon arrival at the ECX before being auctioned to the highest bidder. Coffees are purchased through the Ethiopian Commodity Exchange (ECX), which accounts for over 90% of Ethiopia's coffee production, commodity price forecasting aims to develop predictive models that forecast the prices of commodities like coffee properly. There are different brands of coffee exported as a cash crop. Some of them are discussed below.

Jimma Coffee: Ethiopian coffee is produced in enormous quantities in this region in the southwest of the country. The share of income obtained from coffee among the total income of the coffee-producing district of the Jimma zone is 77% (Diro et al., 2019). Many of the coffees produced in this region are of commercial quality. It is not only a source of money in this region but also a means of subsistence for the area's small-scale producers. Jimma coffee has a light to medium body, a stronger acidity, and a variety of taste nuances. The majority of Ethiopian coffees are naturally processed, which means the cherry fruit is still attached to the coffee bean after it is dried (Kassaye et al., 2018). Fruity or winey tones and bright acidity are produced by this kind of processing.

Yirgacheffe Coffee: Yirgacheffe is part of the Sidamo region in southern Ethiopia, which is known for coffee. The majority of Yirgacheffe coffee is grown at elevations of 2,000m or higher

(Adane & Bewket, 2021). Farmers in the Gedeo Zone produce coffee in high numbers (52%), according to Adane& Bewket (2002). Yirgacheffe produces mostly washed coffees, but it also produces a limited number of sundried coffees and is among the best coffees in the world. Many coffee consumers seek organic coffee with a fruity-forward flavor, which is created by the variety, environment, and processing method. Yirgacheffe coffee plants flourish in Ethiopia's humid climate. The Ethiopian commodity exchange exports this coffee to the foreign market as one brand.

Harar coffee: This is one of the highly exported Ethiopian coffees, which is highly exported to earn income for Ethiopia. It was one of the original 'grades' of Ethiopian coffee. Harar coffee is known for its highest quality. Harar coffees are now largely sourced from wild native trees on tiny farms in the country's east, where they are dry-processed and classed as long berries (big), short berries (smaller), or Mocha (pea berry). Harar coffee's flavors range from a lot of blueberries to a variety of flavors like banana, strawberry, and bubblegum.

Wollega Coffee: Wollega is one of the zones known for the production of coffee arabica. In Kelem Wollega Zone's Anfillo District, coffee arabica is widely grown by homes beneath a variety of shade plants. Kelem Wollega, East Wollega, and Gimbi coffee are known as Wollega coffee or Nekemte coffee. Wollega coffee is recognized for its fruity flavor that ranges from medium to robust. Ethiopia's commodity exchange takes those coffee commodities and grading, sampling, and weighting are performed based on their types. Agricultural commodities are sold by smallholder farmers to local merchants, who then sell them to distributors and collectors, and collectors sell them to suppliers who export via the ECX. Cooperative unions sell directly on ECX. Producers must submit crops to the inspection center before listing on the exchange

Sesame: It is one of the major agricultural commodities that Ethiopia produces and exports to the international market. It is one of Ethiopia's most important commercial grain crops and agricultural products. Sesame is an oil seed that Ethiopia has been producing in the northern areas of the country, mostly in the Tigray and Amhara regions, particularly in the Gondar area, Benshangul-Gumuz region, Oromia region, and especially Wollega. According to the central statistical agency of Ethiopia (CSAE), 18% of sesame seed is produced for export purposes. Ethiopian sesame markets are inextricably tied to the international market and extremely volatile in response to shifts in global supply and demand. This commercial commodity has been exported to different foreign markets like China, and Asian countries like Pakistan and India. Sesame is ready to be exported through the Ethiopian commodity exchange.

Among exported commercial crops After coffee, sesame is the second most profitable export to the international market according to information from the Ethiopian commodity exchange authority(Eshetu & Mehare, 2020). This agricultural commodity is produced in a different part of Ethiopia. These areas are:

Sesame production in Metekel and Assosa: This type of sesame crop is produced in Benishangul-Gumuz, which is located northwest of Ethiopia, bordering Sudan (Kostka & Scharrer, 2011). Sesame-producing districts such as Metekel and Assosa are well known. Although sesame growing is considered a smallholder activity, large-scale private investors are increasingly joining the market in response to the Ethiopian government's Growth and Transformation Plan, which promotes large-scale agriculture to expedite growth. The Benishangul Gumuz Regional Agricultural & Rural Development Bureau does not have precise data on the number of smallholders and large-scale investors. According to other interviews, smallholder farmers account for more than 90% of sesame growers.

Humera sesame seeds: The flavor ark. This unique artisanal oil was once made in northern Ethiopia, in the Humera region of Tigray. Commercial sesame seed production is well-known in this area. One of the settlements in Humera has a community camel-powered oil extraction system. This type of commercial commodity grows in Humera, Metema, and Gondar.

Wollega sesame Seeds: Wollega sesame is a whitish sesame type that is suitable for oil crashing. Ethiopian origin, minimum purity of 99 percent, minimum oil content of 55 percent, maximum moisture content of 6%. Those commodities are exported to earn income and to change the life of farmers. Ethiopia commodity exchange collects those commodities from producers and connects traders and producers.

Green mung beans: Green mung bean is also among the commercial commodities that Ethiopia exports through the Ethiopian commodity exchange. Mung bean productivity in Ethiopia is predicted to range between 12 and 15 qt/ha on average, with annual production increasing. The Amhara and Benishangul Gumuz regions are two prospective green Mung bean growing places. This commercial crop is known as "Masho" locally and is harvested in north Shewa, the south

Wollo zones of the Amhara region, and some of the Benishangul-Gumuz region. Green Mung bean is widely consumed in other countries, but it is rarely consumed in Ethiopia, even by those who grow it. It is only grown to make money by selling it to exporters. Approximately 90% of overall production, according to regional agricultural bureaus and market participants, is a marketable surplus. This commercial crop is exported to different world markets to generate income for Ethiopia next to sesame seeds. The well-known export destinations of green mung beans from Ethiopia are Indonesia, the United Arab Emirates, Singapore, and India. The green mung bean was installed as one commodity for export on the Ethiopian commodity exchange on January 22, 2014. The decision to add green mung bean to the Ethiopian commodity exchange was passed in July 2013 after the Board of Ethiopian commodity exchange authority's approval. Green mung beans were the ideal choice for the exchange because they are a commercial commodity with a low cost of production. Green mung is a type of mung that is produced in a short period, usually 75 to 90 days. The green mung bean has been categorized into green mung bean shoa and green mung bean Asossa types.

Therefore, this research is intended to anticipate the price of those agricultural commodities using a deep-learning approach to address the challenge of predicting the price of commodities in the future.

1.2 Motivation of the study

The price of commodities fluctuates from time to time in our country, Ethiopia. This change in commodity prices is affecting the living standards of millions of Ethiopians especially producers. It affects the market equilibrium (a state in which market supply and demand balance each other) and our country's gross domestic product (GDP) (Gebremeskel, 2020). Farmers, who take on a variety of responsibilities in crop production, are likewise impacted by the volatility of commodity prices. Due to a lack of knowledge about the path the market will take in the future and the possibility that they will produce a crop that is not in demand on the domestic or international market. This is due to no more reliable way to connect buyers and sellers efficiently to discover market prices. Unexpected changes in commodity prices also affect economic analysis and are the main problem of economic inflection in our country (Nuru & Gereziher, 2021). Many people’s traditional prediction ways, which do not follow systematic methods. Such a traditional estimation method leads to a wrong and unproven conclusion.

To alleviate the above-mentioned problem, deep learning techniques have taken attention for forecasting the price of agricultural commodities. One application of machine learning is price forecasting using time-series historical data, and it inspired me to use this method to address the issue of commodity price prediction. The prediction of agricultural products is used to understand the market trend in the present and the future using deep learning algorithms like long short-term memory, gated recurrent unit, and bidirectional long short-term memory, which can learn from historical data the trend of prices. Deep learning is a sub-branch of machine learning that will provide good performance as our data increases. This price forecasting using deep learning techniques predicts the price of commodities in the future to take a proper measure which will be used to control the fluctuation of commodity prices in the future. Productivity can be enhanced by understanding an unexpected increase or decrease in price accurately in the future (Manogna & Mishra, 2021). It can provide information for farmers on which type of crop they have to harvest to increase their income. It is also used by the government to make agricultural policies depending on the predicted price of agricultural commodities. This study will give market price information to concerned traders. The result of this study can also be used in stock price prediction and other financial institutions (Hiransha et al., 2018) (Kumar et al., 2019a).

1.3 Statement of the Problem

The primary economic sector in Ethiopia is agriculture, which accounts for a greater share of GDP than any other sector (Khairo et al., 2005). This agricultural production accounts for more than 85% of the total export commodity income of Ethiopia. The Ethiopian commodity exchange (ECX) is the marketplace where sellers and buyers meet to trade those commodities. This organization has been working on different agricultural commodities like coffee, sesame, soybeans, green mung beans, red kidney beans, and maize. Predicting the future price of those commodities is a crucial problem for the organization. Providing market information without pre-prediction of commodity's price is the key issue. Even though ECX working on different commodity like sesame, and green mung beans the forecasting of those commodity prices is challenging (Gebisa, 2019). This problem is challenging agricultural commodity production. Farmers, who are the main producers of the commodities, are affected financially and have no way to know at what time they have to sell their commodity and no scientific method to inform the commodity producer to schedule which type of commodity they have to harvest in the future (Nuru & Gereziher, 2021). The Ethiopian commodity exchange mainly focuses on trading and preparing commodities of high quality for export trade. But this is difficult due to no means of price prediction methods. Ethiopian exports are mainly concentrated on agricultural products, which are affected by the sharp fluctuations of internal and external factors like price volatility. However, there is no systematic methodology to forecast the future market direction concerning the international market and adjust market direction. Unconditional changes in commodity prices affect the country's growth domestic product (GDP).

The market equilibrium is troubled by the fluctuation of agricultural products when the produced commodity and demand do not balance each other due to a lack of forecasting of the commodity price (Khairo et al., 2005) (Rezaei et al., 2021). One of the economic development plans in Ethiopia is enhancing linkages between agricultural producers and commodity markets, which is affected by the absence of price prediction (Teddy Tefera, 2021). The people who give traditional or oral deductions of commodity prices in the future will not give valuable insight. It is tedious and provides unproven results (Kumar et al., 2019b). This leads to considerable risk in the process of price modeling and forecasting (Jha & Sinha, 2013a). Without predicting the future price of a commodity, trading is not conveying a productive outcome.

The contributing factors of commodity price fluctuations are like demand and supply, weather condition and quality of the products that produced by the farmers. According to (Bindera,2009) the price of agricultural commodity in Ethiopia volatile due to lack of grading, lack of trade finance and market promotion. IF the price of agricultural commodities is not properly forecasted, staying in sync with the market and improving the effectiveness of the sales process becomes difficult (Sabu & Kumar, 2020). Farmers shift from cultivating those commodities to other cultivations because of price fluctuations and lack of proper forecasting. Most of price forecasting study conducted by researchers (Amin, 2020) (Nassar et al., 2020) focused on short term prediction, but it is difficult to use it in planning of future price in a year.

Therefore, the contribution of this study is to solve the problem of commodity price forecasting using deep learning techniques, which can forecast the future price of those agricultural commodities using the previous year's historical data, which were collected from the Ethiopian commodity exchange.

1.4 Research Questions

To achieve the objectives of this study, an attempt will be made to answer the following basic research questions:

RQ1: How to improve the performance of commodity price forecasting model?

RQ2: Which neural network will provide high accuracy for this predictive model?

RQ3: Which evaluation metrics will provide more accuracy for the developed deep learning model that will be used for commodity price forecasting?

1.5 Objectives of study

1.5.1 General Objective

The general objective of this study is to design and develop a predictive model which used to forecast the price of a commodity using deep learning techniques.

1.5.2 Specific Objective

The specific objective of this study is:

- ❖ To review the concept and related works on price forecasting as well as those about machine learning techniques in price prediction.
- ❖ To add hyperparameter tuning to recurrent neural network to optimize the model.
- ❖ Identifying the relevant set of features from the collected dataset for price forecasting.
- ❖ Collecting data from Ethiopian commodity exchange about the commodity price trends
- ❖ To train the price forecasting model on a collected dataset.
- ❖ To evaluate the model performance using regression algorithm evaluation metrics for test data.

1.6 Significance of the Study

Price changeability is a challenging problem in the trade sector that our country, Ethiopia, is phasing out (Gebremeskel, 2020). Commodity price forecasting is used to predict before prices fluctuate or to take corrective measures before unconditional changes take place. The main application of this forecasting is for farmers, who play a great role in our country's economy by producing goods. Predicting the commodity price helps the farmer to schedule which type of crop they have to sow based on market direction. Accurate agricultural harvest price forecasting can have a significant decision-making footprint for the suppliers. (C. O. Ribeiro & Oliveira, 2011). Productivity will be improved by understanding the commodity price (Kurumatani, 2020). Policymakers will use the results of this study to prepare the national agricultural policy. The prediction of commodities is also used to know the international market price direction to adjust our country's policy. In economic analysis, price forecasting is used to control the equilibrium quantity (the situation in which there is no shortage of commodities or surplus of products in the markets) and is used to test the international market to reduce its impact on our economy. Price forecasting could aid the agriculture supply chain in making the appropriate decisions to reduce and manage the risk of price fluctuations. This study helps governments to take corrective measures before the rate of price increases alarmingly and makes people suffer from domestic equilibrium (Gebremeskel, 2020). In short, the significance of this study is:

- Enables buyers and sellers to discover market price information easily.
- Used in planning and decision for price risk management.
- Allows farmers to know the price of commodities easily.
- To understand prevailing market trends.
- To attract customers and maximize sales by creating price transparency.

1.7 Scope and limitations

1.7.1 Scope of the study

This study aims to model commodity price forecasting using a deep learning algorithm to enhance prediction prices before the fluctuation is undergone. The forecasting of product prices in the case of the Ethiopian commodity exchange focuses on three top export agricultural commodities, which are widely produced in our country. This study focuses on forecasting export agricultural commodities. Those commodities are coffee, green mung beans, and sesame and the historical data of six years was used for this study. Three deep learning algorithms which can memorize past historical data like LSTM, GRU, and BILSTM will be used to build the predictive model.

1.7.2 Limitations of the study

Even though there are many agricultural commodities produced in our country, this study is limited to predicting only the prices of commodities on which the Ethiopian commodity excha nge (ECX) is working. The Ethiopian commodity exchange is not working on agricultural comm odities like sorghum, teff, and barley. So, the prediction of this study not included those agricultural commodities. The grading of commodity and decision-making is not included in this study. This study focuses only on prediction and does not deal with the natural factors that affect the production of commodities like natural disaster and outbreak of emergency outbreak which highly affects the price of the agricultural commodity. Due to time limitation, developing a mobile application or web application prototype which enable the user to access easily is not built.

1.8 Application of Result

The main applications of this study are in agriculture and the financial sector like the market to identify the future direction of prices. This study focuses on forecasting the price of agricultural commodities. Farmers use the result of this study to harvest the commodity which is highly needed in the market based on the price predicted. The agricultural policy maker also uses it to prepare national agricultural policy by determining which types of commodities the country has to harvest to get income from foreign markets (Jha & Sinha, 2013b). To control the fluctuating price of commodities, trade and industry sectors also use the results of this study (Gu et al., 2022). Price forecasts would be used by all market players to make educated judgments. Potential landowners can select an appropriate purchase time and find a property with qualities (area, size, etc.) that meet their needs, whereas developers and investors can evaluate predicted return on investment into assets based on a commodity's predicted price.

1.9 Organization of the Thesis

The organization of the study is the overall content of the study which was conducted to reach the desired result. The organization of the commodity price forecasting using dep learning is discussed below:

Chapter one: This part of the study is used to describe the introduction part of the study which introduces the general idea of this study like the motivation of the study, statement of the problem, the objective of the study, research question, scope, and result of the application of the study deliberated in this section.

Chapter Two: Is the most essential part of the study which deals with the literature review and related work of this study. A literature review helps us to get a supportive idea and to analyze the existing system to gain a further understanding of the study area. A literature review is used to indicate what other researchers have already done to bear their limitations to the present study.

This chapter focuses on the consideration of the subject matter, methodology, and design of the study. The formation of the problem statement or the object of the investigation is the focus of the literature review. This chapter is regarded as the study's balance chapter and is used to identify the gap in related work conducted previously in the area.

Chapter Three: This section of the study discusses the study's avenue of research. The method and technique applied in this research to design the intended solution are referred to as research methodology. The first portion of this section discusses the methodologies utilized in the study, such as data collecting, analysis, and processing procedures, while the second section deals with the model used in this study and the third part of this section are about the instruments used in the study and performance evaluation measures

Chapter Four: This section focuses on designing the architecture of the proposed model of commodity price forecasting. it is used as input for the implementation of the model. This is because the implementation of this study follows the designed architecture in this chapter.

Chapter Five: This chapter's analysis and results are described to draw the interpretation of the study. The result and discussion describe the implementation and experiment of the proposed solution. This section focuses on two parts; The first part is the result of data collection, data preprocessing performance evaluation, model building, and model evaluation described here. This chapter aimed to provide the original work of the researcher along with its contribution. The second part is about the discussion of the result obtained in section one. The obtained result is interpreted and discussed in detail by comparing it with previous work to provide evidence of the contribution of the researcher. The general outcome of the study will be clearly explained in the discussion part of this study. The importance of the study and its shortcomings of the study is discussed here to show the implication for future work.

Chapter Six: This is the final section of the study which provides the general conclusion idea of the research work and the recommendation that other researchers have considered. The findings and conclusion of the study should be summarized and reported clearly. The conclusion tries to mention what is done and how it is done with steps followed to reach the outcome in summary forms. The challenge and the finally obtained result techniques are explained here. In the recommendation part giving information for the user of this study and what the other researcher have to include to enhance this study is mentioned.

CHAPTER TWO

2 LITERATURE REVIEW AND RELATED WORK

2.1 Overview

This section of the study focuses on the way scholarly articles, journals, and surveys related to price forecasting in general and price forecasting of the agricultural commodity for sesame, coffee, and green mung beans using deep learning are surveyed. Literature review enables us to understand the problem in price forecasting, identify what other researchers conducted, and identify the strength and shortcomings in the related works to solve it in the proposed system.

2.2 Overview of Price Forecasting

One goal of data analytics is price forecasting, which would be the skill of forecasting what might take place in the future. Based on the expertise and available external data, the forecaster must select the most effective methodology for forecasting (Gashaw, 2019). Given the availability of data in developing economies, a recent development in the Artificial Neural Network (ANN) modeling approach gives a viable price forecasting technique (Jha & Sinha, 2013a). The main task of forecasting is to use historical data to train machines and predict unknown future values of interests.

2.3 Why Commodity price forecasting

Agricultural commodities are a key source of export revenues for many countries, including Ethiopia, and commodity price swings have a significant impact on overall macroeconomic perfo rmance (Gebisa, 2019). As a result, commodity price projections are an important component of macroeconomic policy formulation and planning. Using a neural network algorithm, price prediction assesses a product or service based on its attributes, demand, and current market trends. The machine then estimates a price strategy that will both attract customers and increase sales. Farmers also benefit from price projections since they base their production and marketing decisions on predicted prices, which can have long-term financial consequences. The major benefit of forecasting is that it provides the business with useful information that it can use to make decisions regarding the organization's future. In many circumstances, forecasting is based on qualitative data and expert judgment. But this study focuses on quantitative data. Accurate agricultural commodity price forecasting would help to mitigate the risk associated with price changes (Gu et al., 2022). Commodity price prediction is crucial to economic development and product future prices have an impact on the fluctuation of market prices, which leads to instability in the economy.

2.4 Overview of Machine Learning

According to Artur Samuel, machine learning is "a branch of study that gives computers the ability to learn without being explicitly programmed." A machine learning application allows computers to access data and use it to learn from one another. It is the technology that allows the machine to learn automatically from past historical data. A machine learns from historical data based on complex mathematical criteria and can tackle unpredictable circumstances at runtime (Fite & Science, 2021). Machine learning is the study of making computers more human-like in their behavior and decision-making by empowering them to learn without explicit programming or with minimal human intervention.

Today, the need for machine learning is increasing due to the increasing complexity of problems that cannot be solved by human beings. Machine learning approaches are a collection of mathematical models for solving issues with high non-linearity, such as prediction, classification, data association, and data conceptualization. In particular, machine learning techniques can be used to forecast the number of products or services that will be purchased in the future. In this circumstance, data can be used by software to enhance analysis. Machine learning forecasting is unquestionably the method and path forward for achieving high forecast accuracy. Machine Learning Forecasting allows processors to learn from massive amounts of data without the need for human intervention, resulting in unequaled customer demand insights. In forecasting, machine learning has the following role:

- Provide a more accurate forecast
- Analyze more data
- Identify hidden patterns in data
- Automate forecast updates based on the recent data
- Create a robust system

Machine learning algorithms are grouped into four categories depending on their learning capabilities and how the algorithm works on a dataset. These are supervised machine learning, unsupervised machine learning, semi-supervised machine learning, and reinforcement machine learning. A supervised machine learning algorithm takes labeled input data and known responses to data as output. The main goal of supervised machine learning is the mapping of input data with output data. In supervised learning, the labeling of data is important and should be labeled before using data. The unsupervised machine learning algorithm works on hidden patterns or internal structures of unlabeled data, and the machine learns by itself without a human supervisor. The main goal of unsupervised machine learning is the grouping or clustering of data into new groups of objects with similar patterns. Semi-supervised learning is learning from labeled and unlabeled data. The algorithm is designed for the problem, which involves a small number of labeled and a large number of unlabeled examples, from which the model must learn and provide proper prediction on new examples while testing. Reinforcement learning is different from the above learning mechanisms because in reinforcement there is the concept of feedback-based learning [1]. The agent is rewarded for each correct action and punished for each incorrect action in this learning strategy. To increase their performance, the agents must learn automatically based on feedback. The following is a simple Reinforcement learning diagram.

Figure 2.1 Reinforcement learning diagram

Different types of machine learning with their type of data set are shown in the below diagram.

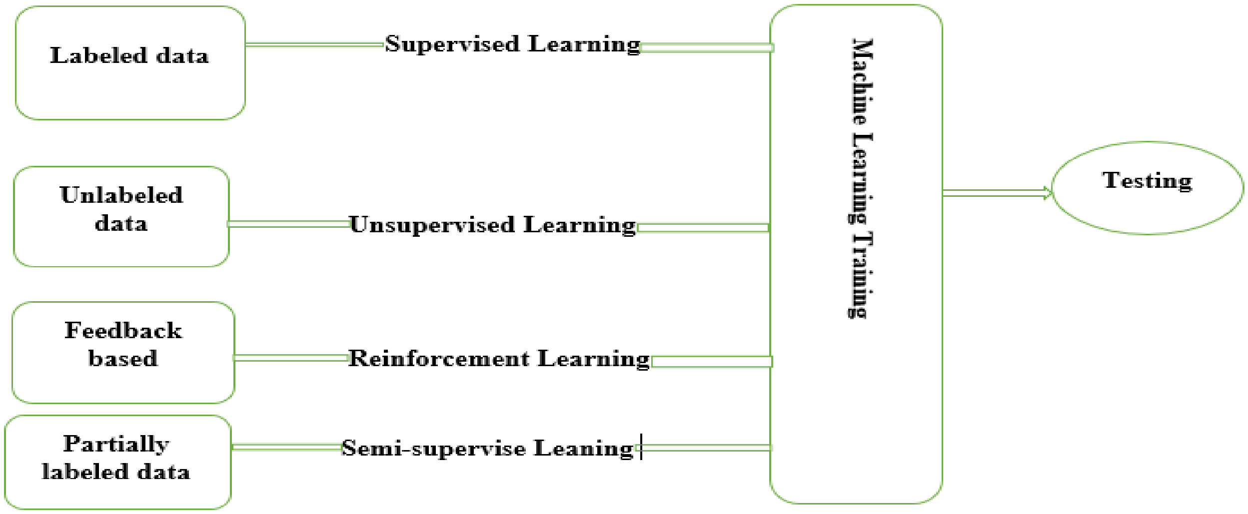


Figure 2.2 Types of Machines Learning according to their training data type

Even though machine learning can perform prediction or inference based on questions and available data, the performance of machine learning may not increase as data increases after a certain point of time. This problem is solved in a new branch of machine learning, which is known as deep learning algorithms. Deep learning is a complex multilayered algorithm that can learn by itself, unlike machine learning. It is a type of machine learning that gets supremacy in accuracy over machine learning when it is trained on big data and can learn high-level features from a given big dataset (Amin, 2020). It is also used to reduce the need for domain expertise for feature extraction. This is what inspired me to use deep learning models for commodity price forecasting, which have a large dataset. In deep learning techniques, learning takes place via neural networks, and each layer is stacked on top of the other in a hierarchy of increasing abstraction and complexity. Different deep learning algorithms are used for the prediction of future prices. To determine which algorithm will provide the highest performance among different deep learning techniques, it is better to train and test the model. But Most researchers get high performance using artificial neural networks in this area (Siami-Namini et al., 2019) (C. O. Ribeiro & Oliveira, 2011). But there is no exact algorithm assigned to a specific problem; rather, it depends on the type of problem and the need to practice it first. Based on this suggestion, this study will use some known artificial neural networks to predict the price of commodities on Ethiopian commodity exchanges.

2.4.1 Artificial neural network (ANN)

An artificial neural network is a computing system lightly inspired by the structure of the human brain (Jha & Sinha, 2013b). It is employed for complicated studies in a variety of disciplines, from engineering to medical and a computational model made up of various processing components that process inputs and produce outputs in accordance with predetermined activation functions. ANN uses a layered approach to process information and provide the decision. This neural network has three layers, each of which has its role in completing overall tasks from input layer to output layers. The first layer is the input layer, which is used to take external data into artificial neural networks (Deressa, 2014). The second layer, known as the hidden layer in which the input from the first layer is processed to passed to the next layers. The complexity of an artificial neural network increases as the number of hidden layers increases. The final layer is output layer where the desired prediction is displayed or obtained. Among different types of neural networks, for this study we will used LSTM, GRU and BILST because most of the previously conducted study obtained high accuracy using on time series problem (M. H. D. M. Ribeiro et al., 2019) (J. Wang & Li, 2018) (Gu et al., 2022). These neural networks are discussed below.

2.4.2 Recurrent neural network (RNN)

A recurrent neural network is an artificial neural network in which the output from the previous step is fed as input for the current step (Bouktif et al., 2018). In traditional neural networks, there is no concept of using previous output as input for the current step, and input and output are independent of each other. In the case of predicting the future price, the previous price is required, and hence there is a need to remember the previous data. Unlike multilayer perceptron, RNN takes input from two sources. One of the inputs comes from the past and the other comes from the present (Hiransha et al., 2018). In the computation process of RNN, each neuron is used as a memory cell. The recurrent neural network (RNN) is an artificial neural network that can memorize. It works on sequential data or time series data (ordered data in which similar data follow each other) and can share parameters across all networks. Even if an RNN model has memory, most of the time it suffers from gradient vanishing and exploding problems. When utilizing TANH or RELU as an activation function, RNN won't be able to process very long sequences. This means its memory is short-term memory, which can forget history if historical data attribute increases. This problem is solved in long-term short-term memory (LSTM). The sequential processing of the recurrent neural network is shown in the diagram below

.

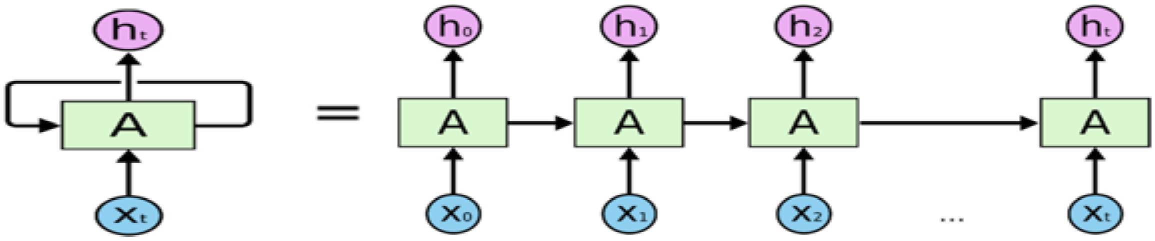


Figure 2.3 Recurrent Neural network Processing (Le et al., 2019)

The RNN shown on figure 2.3 have the following equation.

$$\boxed{\mathbf{h_t = f_n\ (W_{xh}X_t + W_{hh}\, h_{t-1} + bh)}}$$

Equation 2.1 Sequential Processing RNN Equation

where ht: Hidden layer at the ith instant, fn: Function, Wxh: Input to the hidden layer, $\mathbf{X_t}$: input at ith $\mathbf{h_{t-1}}$: hidden layer at t-1th, $\mathbf{b_h}$: bias value or threshold values. Another equation of RNN is an equation from the hidden layer to the output layer.

$$\boxed{\mathbf{Z_t = fn\ (W_{hz}h_t + b_z)}}$$

Equation 2.2 Equation from hidden layer to the output layer

$\mathbf{Z_t}$: **output**, $\mathbf{W_{hz}}$: hidden to output layer weight, $\mathbf{b_z}$: bias value or threshold values.

2.4.3 Long short-term memory (LSTM)

One type of RNN capable of learning long-term dependency is long short-term memory (Hiransha et al., 2018). It is a type of artificial neural network that uses a series of gates to govern how data in a sequence enters, is stored, and exits the network gates. In LSTM, the problem in RNN, which is the exploding gradient and vanishing problem, is solved by introducing forget gates, which can remember history by extending their memory in recurrent neural networks (Siami-Namini et al., 2019). This algorithm can learn from its long-time experience, unlike RNN. Long short-term memory is used to make RNN remember inputs over a long period (Bouktif et al., 2018). The LSTM contains three gates: an input gate, a forget gate, and an output gate. An input gate is used to determine whether a new input is in or not. The second gate is the forgetting gate, which is used to avoid or delete information that is not important. The main task of the forget gate is to determine to what extent to forget the previous historical data. An output gate has to determine what output is to be generated at the current time step. Figure 2.5 is the flow diagram of an LSTM with Ct-1 is old cell state, Ct is the current cell state, ht-1 is the output of the old previous cell, ht is the output of the present cell, it is the input gate layer, ft is for the gate layer, and **Ot** is output at the sigmoid gate layer (Hiransha et al., 2018). RNNs with long short-term memory is created to solve the problem of short memory in RNNs. It has components called gates, which have the role of regulating the flow of information. A simple diagram that shows how long short-term memory (LSTM) works and how each state works from the input layer to output layer is shown below.

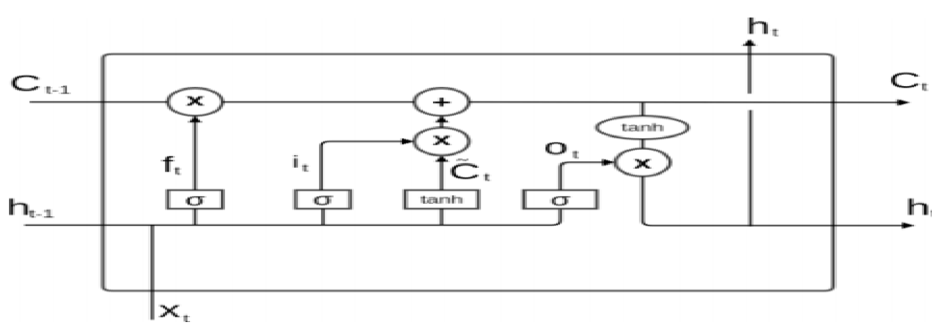


Figure 2.4 Flow diagram of LSTM cell (Hiransha et al., 2018)

The cell state (**C_{t-1}**, C_t) is used to carry information from the previous cell state to the current cell state. Forget layer(**f_t**) have the role of deciding where the information is stored.

2.4.4 Bidirectional Long short-term memory (BLSTM)

In RNN and Simple LSTM, information and memory persist only in one direction or moving forward only. Those models are trained and learn only on structure and dependence that move in one direction, which is the forward direction. This problem is solved with bi-directional long-term memory (BLSTM), which includes the bidirectional wrapper for RNN and Simple LSTM. Bidirectional LSTM is an extension of long-term memory (Baharudin, 2021). Unlike LSTM, two models are introduced in BLSTM (S. Wang et al., 2019). The preceding and following input sequences of data were used in BLSTM to fully utilize all input data and achieve the greatest learning process performance (Althelaya et al., 2018). The first model, which is a forward model, learns the sequence of input provided and the left one works on the reverse of the first one. The two models are combined using a mechanism called the "merging step. The merging step in the BLSTM model is conducted using sum, multiplication, averaging, and concatenation. A simple diagram that shows bidirectional LSTM is shown below.

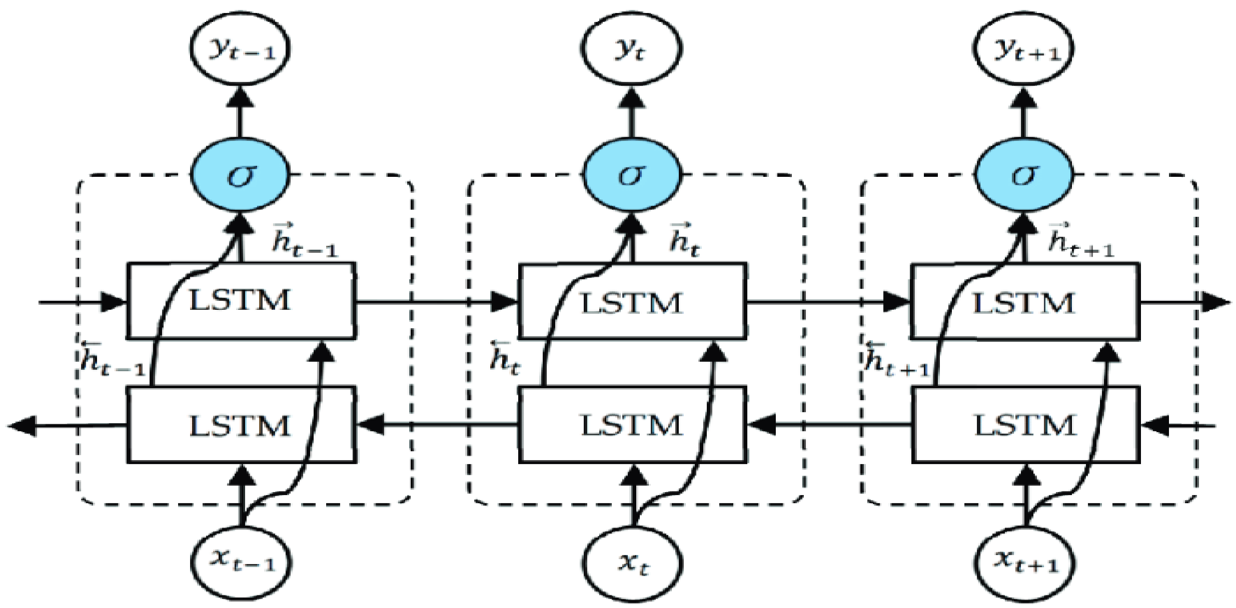


Figure 2.5 Bidirectional LSTM

Adopted from[1]

As shown in figure 2.6 above, the input X$_t$ **-1, Xt, and Xt+1** in the forward layer and back ward direction combined to provide the output**.** The output is shown by Yt-1, Yt, and Yt+1 after being

[1] https://www.researchgate.net/figure/The-unfolded-architecture-of-Bidirectional-LSTM-BiLSTM-with-three-consecutive-steps_fig2_344751031

combined with the merging technique. This model works on historical time series data and we used it for price forecasting purposes.

2.4.5 Gated Recurrent Unit (GRU)

(Chao et al.) introduced the GRUs model in 2014. This neural network is used to solve the vanishing-exploding gradient problem in recurrent neural networks. It adjusts neural network input weights to handle the gradient vanishing problem (Shen et al., 2018). The capacity of memory in RNN is improved in GRU and it provides easy training of the model. One advantage of GRU is the ability to keep long-term dependencies in sequential data. Unlike LSTM, GRU has only one hidden state transferred between time steps. This hidden state is used for holding both long-term and short-term dependents. The update gate and the reset gate are two gates in GRU that are used to selectively filter out irrelevant data while maintaining important data. The two gates have two values of 0 and 1 that are multiplied with the input data or hidden state, with 0 indicating that the data in the input data or hidden state is unimportant and 1 indicating that the data is important and will be used in the future.

Reset Gate: The reset gate is calculated from the previous timestep and the current input data. The prior hidden state and current input were multiplied by their weights and summed before being passed via a sigmoid function. The task of the sigmoid function is to transform the value between 0 and 1 to filter importance as more important or less important information in the subsequent steps.

$$gate_{reset}=\sigma(W_{input_{reset}}.x_t+W_{hidden_{reset}}h_{t-1})$$

Equation 2.3 Equation for reset gate

Update Gate: This gate is used to assess how much historical information must be passed on to future generations. It is used to solve the problem of vanishing gradient. This Update gate is calculated using the previous hidden state and current input data.

$$gateupdate=\sigma(Winputupdate\cdot xt+Whiddenupdate\cdot ht-1)$$

Equation 2.4 Equation of Update gate

The update gate will undergo element-wise multiplication with the previous hidden state to obtain u in the equation as follows: $u=gateupdate\odot ht-1$

Finally combining the output gate will take place to get updated hidden states. All these functions of the gated recurrent unit are explained in the diagram below.

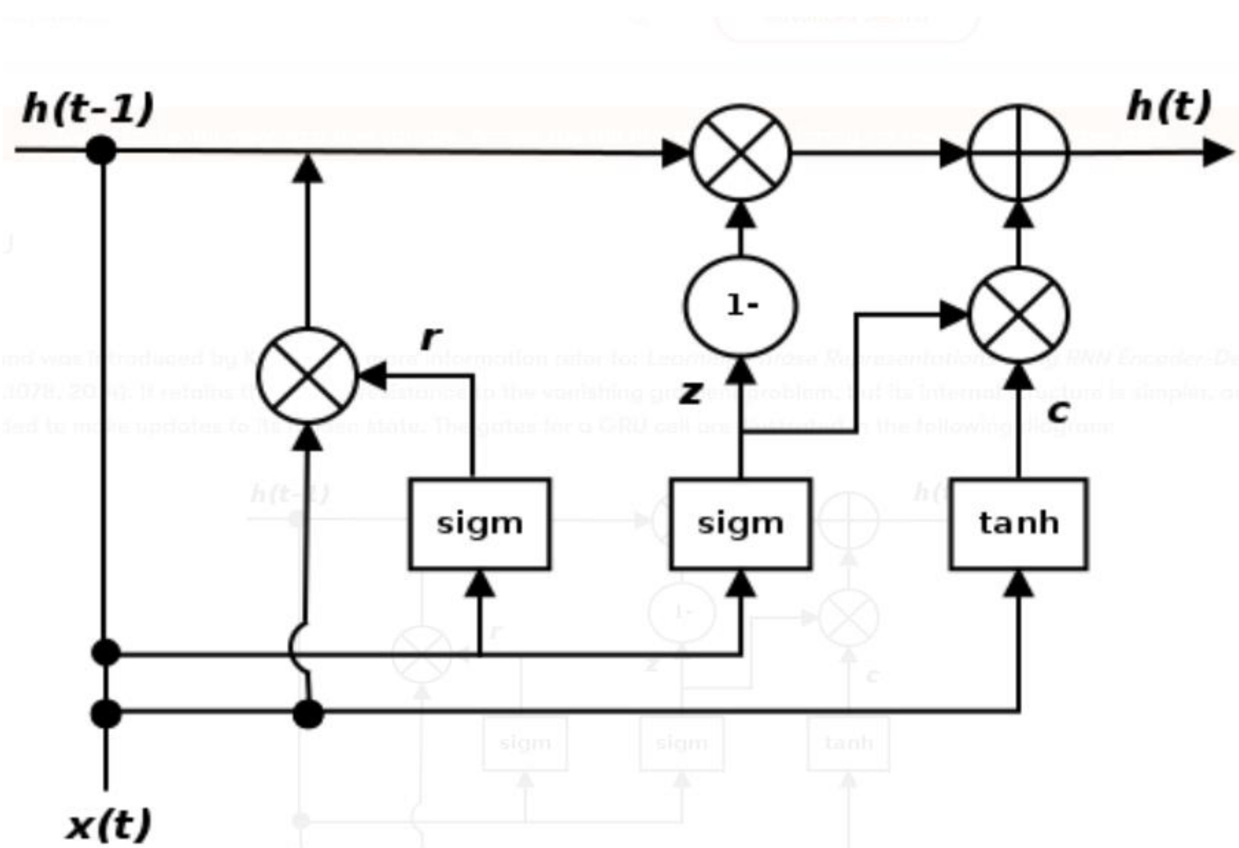


Figure 2.6 Gated Recurrent Unit (Adopted from K. 2014

As shown in the above diagram, GRU does not have a separate cell state like LSTM. The model uses only hidden states instead of separate cells. This makes the GRU structure simpler and faster to train the model. As shown in figure 2.7, GRU takes input Xt at each timestamp t, and a hidden state, which is represented as ht-1 from the previous timestamp t-1. Finally, the model provides the hidden state Ht as an output which is passed to the next timestamp for further processing.

2.5 Application of Machine Learning in Price of Commodity forecasting

One application of machine learning is price forecasting. Machine learning techniques allow for the prediction of the price of commodities in the future. Based on previous data, machine learning model predictions allow organizations to generate highly accurate guesses about the potential outcomes of a question. Machine learning is used to predict the direction of price movement. Machine learning incorporates predictive analytics, a branch of mathematics that examines patterns in current and historical data to forecast the future. The task of machine learning here is to prepare predictive modeling techniques that automate the process by producing training algorithms that look for patterns and behaviors in data without being explicitly instructed on what to look for. The forecasting of commodity prices helps to provide information about the market direction to take important decisions by the government and by users. It is also used to inform the consumer of the appropriate purchase time (Gebisa, 2019). The size of data on which machine learning is trained increases, but the performance of machine learning after a certain level does not increase. To solve this problem, the sub-branch of machine learning, which is deep learning, was introduced. Deep learning outperforms machine learning when data size increases (Gu et al., 2022). Deep learning is more powerful than traditional machine learning since it generates transferrable solutions and algorithms can use neural networks to produce transferrable results. These learning techniques play a great role, especially in the era of big data.

2.6 Related Works

The lack of a price forecasting method to determine whether the price of an agricultural commodity will increase or not to take the correct measure is an immense problem that needs to be solved with the help of a scientific method. Agricultural commodity price forecasting is a hot research area in the economy, and many researchers try to do their studies in this area. Some researchers used traditional forecasting methods. The traditional way to solve the prediction problem is by using linear statistical methods like autoregressive integrated moving average (ARIM), which is shifted to an emerging machine learning technique (Chen et al., 2021). A machine learning technique is used to forecast the price of a commodity to give a future commodity price. As the number of datasets increases, the prediction performance of machine learning has no change after some point. To solve the limitations of machine learning, the advanced techniques of deep learning algorithms have been introduced by many researchers (J. Wang et al., 2019) (M. H. D. M. Ribeiro et al., 2019). With an increase in dataset size, the model learns more and the predictive capability of deep learning also increases.

The prediction of commodity prices is used to make coherent and concise strategic planning (M. H. D. M. Ribeiro et al., 2019). The planning depends on the outcome gained from the forecasting. The author used a combination of machine learning algorithms like K-nearest neighbor, neural network, and extremely randomized tree. However, the researcher used only a small dataset that encountered the model overfitting and forecasted only for three months, which is a short-term prediction.

The fluctuation of commodity prices has a direct impact on the country's economy (Gebremeskel, 2020) (Sabu & Kumar, 2020). The study explained that commodity price changes are the drivers of inflation. The result of their prediction is used as input for the government to make decisions and maintain the economic equilibrium of the country. However, it was not based on empirical results and did not explain what factors affected the price of those commodities.

(Widiyaningtyas et al., 2020) explained how extreme machine learning methods can predict staple food commodities' prices. The author used a feedforward artificial neural network, which has only one hidden layer. However, the study was less accurate and did not use enough datasets to train the machine for more performance. (Ouyang et al., 2019) was introduced to predict the agricultural commodity price using a long-short-term time series network (LSTnet) and obtain better performance than ARIMA. The author explained that global agricultural commodity price forecasting depends on multivariate time series and is very essential for providing price information and used to reduce the risk that arises from agricultural markets.

(Gao et al., 2019) elaborated those recurrent neural networks and long short-term memory, which can remember past historical data, are used to produce higher performance in price prediction. The historical data with time series is collected and the future price of the stock is predicted via a designed deep learning algorithm.

According to (Sabu & Kumar, 2020), the changing price of agricultural commodities has an incompatible effect on a country's GDP. The author used the SARIMA, Holt-winter seasonal method, and LSTM neural network to forecast the price of Kerala. According to the results from the study, LSTM with an accuracy of 92.7%, the Halt-winter seasonal method with an accuracy of 81.9%, and SARIMA with an accuracy of 83.45% were obtained. Based on the result of the study, long short-term memory was obtained as the best model to forecast the price of a commodity named Kerala in India. One of the problems that (Sabu & Kumar, 2020) faced was a lack of data available to train the LSTM model, which is a deep learning neural network that needs a lot of datasets. (Vijh et al., 2020) explained that price prediction in the stock market depends on many parameters, which makes forecasting complex. The author used an artificial neural network to forecast the price based on the closing price of the stock. According to the study, the ANN model provided RMSE (0.42), MAPE (0.77), and MBE (0.013). The limitation of the study was that it did not use traded volume, profit, and loss statements and the author recommended that deep learning models would be developed to solve the mentioned problem.

(Gebisa, 2019), compared different algorithms like LSTM, SVR, and LR and obtained that LSTM is superior to the rest of them in terms of accuracy. The author conducted a study on coffee, which is one of the commodities on which the Ethiopian commodity exchange is working, and used a regression model. However, the study focused only on one commodity. The forecasting of only one commodity cannot be used to decide whether the government is getting a profit from exporting commodities. So, there is the need to include other commodities on ECX working on it currently to control the economic equilibrium of our country, Ethiopia. Various studies on price forecasting areas were conducted by many researchers, with some limitations. The findings and research gaps related to their work are mentioned in the following table.

Table 2.1 Summary of Related Works

no	*Title*	*References*	*Used Algorithm*	*Obtained Results*	*Limitation/future work (Gap)*
1.	Automated Agriculture Commodity Price Prediction System with Machine Learning Techniques	(Chen et al., 2021)	Long short term Memory (LSTM)& ARIMA	Using ARIMA the Price of small data predicted.	- Used small size of data - Short term prediction
2.	Food Commodity Price Prediction in East Java Using Extreme Learning Machine (ELM) Method.	(Widiyaningtyas et al., 2020)	Extreme learning machine	Predicted price of three data with High accuracy.	- Used only feedforward artificial neural network - Small dataset
3.	Agricultural production output prediction using Supervised Machine Learning techniques	(Shakoor et al., 2017)	Decision tree and kNN	Decision tree better prediction for Aman and jute crop Obtained as KNN most accurate	- Limited to fixed Dataset only - KNN not suitable for high dimensional data
4.	Coffee price prediction using machine-learning techniques	(Gebisa, 2019)	CART, SVM, KNN and LSTM	LSTM performed better Than other	- one feature based - Predicted single crop - Short term

5.	Predicting Price of Daily Commodities using Machine Learning	(Amin, 2020)	Support vector machine (SVM)	Ensemble model able to predict more performance	Only daily price of commodity Predicted
6.	Deep Learning Based Approach for Fresh Produce Market Price Prediction	(Nassar et al., 2020)	Combine CNN and LSTM	CNN-LSTM produced a higher performance	Forecast only for short term (10 days)
7.	Seasonal ARIMA to forecast fruits and vegetable agricultural prices	(Dharavath & Khosla, 2019)	Used ARIMA	The predicted price of coming one Month Using ARIMA	No means to hold big data Used traditional modeling (ARIMA) Used classical algorithm
8.	Share Price Prediction using Machine Learning Technique	(Jeevan et al., 2018)	RNN and LSTM	Able to predict stock price very Close to the actual price	Used only 200 days of data Short term prediction Low Accuracy
9	Stock Closing Price Prediction using Machine Learning Techniques	(Vijh et al., 2020)	ANN and RF	ANN out performed with RMSE (0.42) MAPE (0.77)	Not considered finical parameters like trade volume and profit

Therefore, the goal of this study is to address the research gap mentioned in table 2.1. The research gap mentioned in the related work of this study is forecasting for the short term or for daily or weekly and Most of the existing price forecasting was done to predict the short-term price for one day, one week, and using classical algorithms like ARIMA. Another research gap identified is using only one type of dataset to forecast price, which is difficult to evaluate models from varied data sizes. Most of the authors explained that there was a limitation on obtaining data and they used small data sizes. In some papers, the author stated that the other researcher must use deep learning techniques to solve the problem that machine learning techniques failed to solve. Therefore, this commodity price forecasting aims at building a price prediction model using deep learning by improving the problems in the existing system. This research outcome improves the limitation in the previously conducted study; especially in the related work mentioned in the table above. This study focuses on building an accurate and enhanced performance model by tuning the algorithm with hyperparameter tuning and contributing to its role in solving the problem of price prediction in our country, Ethiopia.

CHAPTER THREE

3 RESEARCH METHODOLOGY

The main objective of this study is to forecast the price of the top three agricultural commodities (coffee, Sesame, and green mung beans) to provide market information for producers and exporters. According to (Bizualem & Saron, 2018), those three agricultural commodities account for more than half of the income generated from the foreign exchange of agricultural commodities. Forecasting the price of the commodity to identify the future direction of the goods market is used to take corrective measures by governments or policy makers and producers to sell their predictions at a high price based on the forecasted values. This study focuses on the technical analysis of agricultural commodities to predict the future price using deep learning algorithms like long short-term memory (LSTM), gated recurrent unit, and bidirectional long short-term memory (BLSTM). For this study, the historical data of three agricultural commodities were collected from the Ethiopian commodity exchange, and important features of those data were extracted to build the model used to predict the price. The attributes of coffee, sesame, and green mung bean commodities used in this study are the low price of the day, the high price of the day, the closing price of the day, and the average price of the day which are calculated from those highly correlated features.

Deep learning-based commodity price forecasting is based on time series or sequential data. The time series prediction is difficult since it is a non-binary task and the task of predicting future values depends on the previous historical values and current values. One sub-part of deep learning known as a recurrent neural network used to overcome this problem by going through temporal feedback loops. The current process step's input is derived from the output of a previous step. RNNs can process input sequences without losing track because of this memory. This network is recurrent because of the loops. Therefore, this study solely depends on the neural network algorithm which is one branch of deep neural networks; to forecast the price of agricultural commodities listed above to find out the trend of their price in the future to help both the farmers and traders, Ethiopian commodity exchanges which provide commodity price information for stakeholders and the agricultural sector to prepare national agricultural policy based on the market direction based on the forecasted price of agricultural out puts.

3.1 Research Design

This part aims to develop the overall approaches used to conduct the study and a logical framework to arrive at the suggested solutions. The quantitative research strategy makes use of established metrics, numerical values, and statistical techniques to analyze data. It can be used for phenomena that have numerical expressions. Therefore, this study follows the quantitative approach to perform the experimental method based on data collected from ECX. It is about different types of methodology and the process of developing prediction models for commodity forecasting. This Research methodology includes data collection, analysis, preprocessing, and implementation used to achieve the objective of this study. The following diagram depicts the general workflow to conduct commodity price forecasting using deep learning techniques.

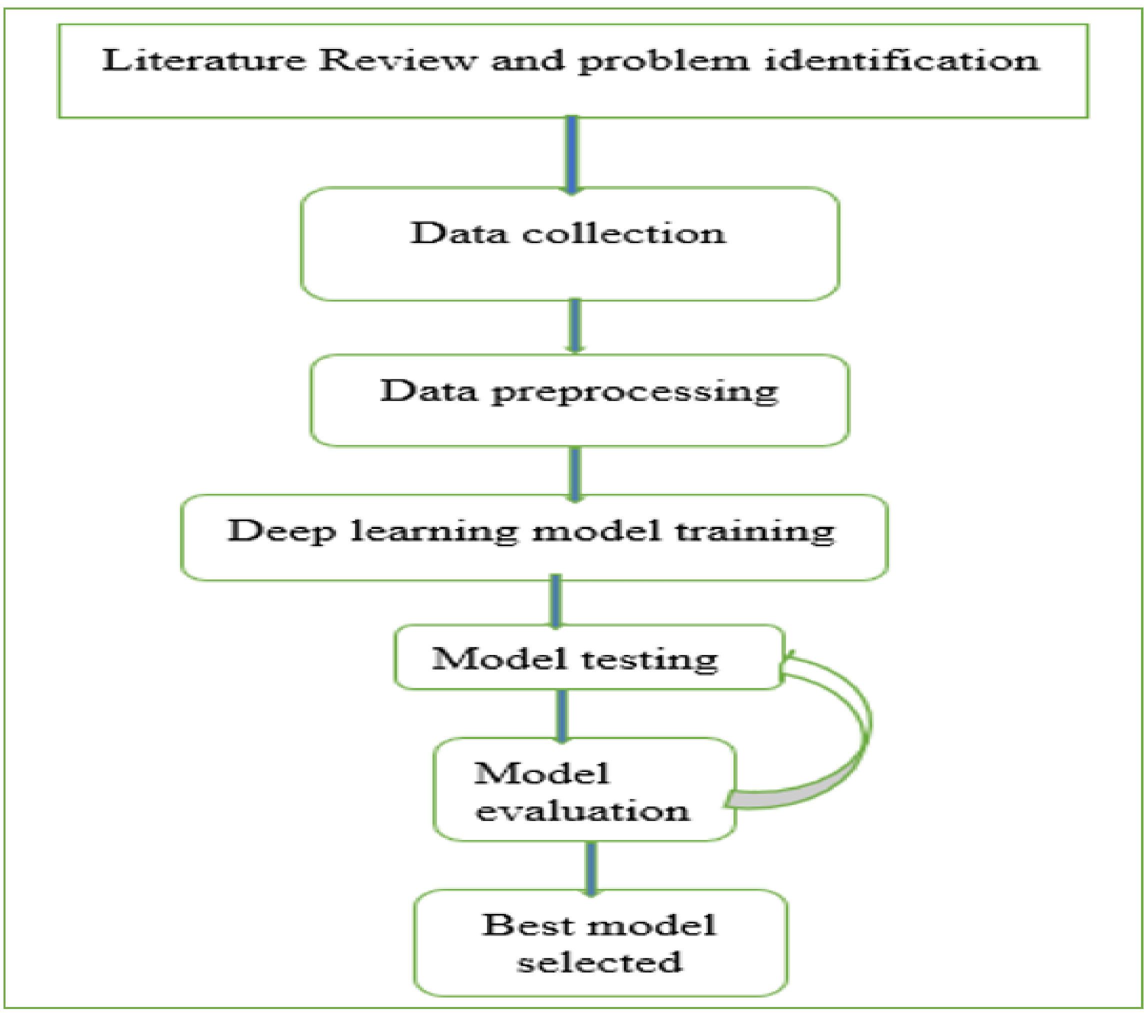


Figure 3.1 Research methodology workflow diagram

3.2 Data Source

The data used to conduct this study was collected from the Ethiopian commodity exchange (ECX). The Ethiopian commodity exchange is the only organization that works on the exchange of a few agricultural commodities by providing the chance to easily sell and buy goods. The historical data of the top three commodities (sesame, coffee, and green mung bean) (Eshetu & Mehare, 2020) was collected and used for this price forecast. The historical data for six years was collected and preprocessed to feed into the model. The rest of the commodities that ECX is working on have fewer data and are not included in this study.

3.2.1 Data Collection

The mechanism of gathering and analyzing accurate data from different sources to feed it into the machine. It is one method of conducting research, which plays an important role in getting quality data. It is the technique of collecting information from relevant sources to answer the study problem. To make sure that the integrity of the study topic is indeed upheld, data collection, whether through quantitative or qualitative methods. It is the quality of collected data that determines the quality of good results, and data collection should be conducted properly.

The data used to forecast commodity prices for this study were obtained from the Ethiopian commodity exchange. Ethiopian commodity exchange (ECX)has a database that stores the historical full information on commodities. To conduct this study data from three top exported agricultural commodities like sesame, coffee, and green mung beans are collected. The number of records collected dataset of coffee is 68561 with eleven columns and the size of the sesame record was 24953 and green mung beans with 3116 records. For each of the three commodities, the historical dataset of six years is collected from the Ethiopian commodity exchange. The rest of the agricultural commodities which the Ethiopian commodity exchange is working on have a smaller number of records and are not included in this commodity price forecasting.

Each dataset collected from the Ethiopian commodity exchange database has eleven features. These attributes are production year, trade date, warehouse name where the commodity is stored, low price of the day, high price, closing price, the volume of the commodity in tons, and percentage change of price from the previous close price. The price of each commodity has been registered for future use by ECX. This study used this dataset to train a model by selecting a few features among the above-mentioned feature based on their correlation values. Each of the data are secondary data because the data was collected by Ethiopian commodity exchange from daily price. The sample of data used for this study is shown below.

Trade Date	Symbol	Warehouse	Production Year	Opening Price	Closing Price	High	Low	Change	Persetntage Change	Volume (Ton)
11/26/2020	WWSSUG	NK	2013	4,645.00	4,645.00	4,645.00	4,645.00	3	0.0%	33.30
11/26/2020	WWSSUG	SG	2012	4,645.00	4,645.00	4,645.00	4,645.00	7	0.0%	80.00
11/26/2020	WWSSUG	SG	2013	4,645.00	4,645.00	4,645.00	4,645.00	7	0.0%	28.00
11/27/2020	WWSSUG	NK	2013	4,649.00	4,649.00	4,649.00	4,649.00	4	0.0%	10.00
11/27/2020	WWSSUG	SG	2013	4,649.00	4,649.00	4,649.00	4,649.00	4	0.0%	9.10
11/27/2020	WWSSUG	WG	2013	4,649.00	4,649.00	4,649.00	4,649.00	0	0.0	7.50
11/30/2020	WWSSUG	SG	2013	4,617.00	4,617.00	4,617.00	4,617.00	32	0.0%	9.60
12/01/2020	WWSSUG	NK	2013	4,620.00	4,620.00	4,620.00	4,620.00	29	0.0%	29.80
12/01/2020	WWSSUG	SG	2012	4,620.00	4,620.00	4,620.00	4,620.00	25	0.0%	17.60
12/01/2020	WWSSUG	SG	2013	4,620.00	4,620.00	4,620.00	4,620.00	3	0.0%	22.20
12/02/2020	WWSSUG	SG	2012	4,627.00	4,627.00	4,627.00	4,627.00	7	0.0%	30.00
12/07/2020	WWSSUG	NK	2013	4,679.00	4,679.00	4,679.00	4,679.00	40	0.0%	30.00
12/08/2020	WWSSUG	NK	2013	4,687.00	4,687.00	4,687.00	4,687.00	8	0.0%	30.00
12/08/2020	WWSSUG	SG	2013	4,687.00	4,687.00	4,687.00	4,687.00	48	1.0%	5.30
12/09/2020	WWSSUG	NK	2013	4,693.00	4,693.00	4,693.00	4,693.00	6	0.0%	13.70
12/10/2020	WWSSUG	NK	2013	4,700.00	4,700.00	4,700.00	4,700.00	7	0.0%	10.00
12/10/2020	WWSSUG	SG	2013	4,700.00	4,700.00	4,700.00	4,700.00	13	0.0%	6.00
12/11/2020	WWSSUG	NK	2013	4,706.00	4,706.00	4,706.00	4,706.00	6	0.0%	7.30
12/09/2020	WWSSUG	NK	2013	4,693.00	4,693.00	4,693.00	4,693.00	6	0.0%	13.70
12/10/2020	WWSSUG	NK	2013	4,700.00	4,700.00	4,700.00	4,700.00	7	0.0%	10.00
12/10/2020	WWSSUG	SG	2013	4,700.00	4,700.00	4,700.00	4,700.00	13	0.0%	6.00
12/11/2020	WWSSUG	NK	2013	4,706.00	4,706.00	4,706.00	4,706.00	6	0.0%	7.30
12/11/2020	WWSSUG	SG	2013	4,706.00	4,706.00	4,706.00	4,706.00	6	0.0%	11.10
12/15/2020	WWSSUG	NK	2013	4,635.00	4,635.00	4,635.00	4,635.00	71	1.0%	11.70
12/15/2020	WWSSUG	SG	2013	4,635.00	4,635.00	4,635.00	4,635.00	71	1.0%	10.00
12/16/2020	WWSSUG	NK	2013	4,641.00	4,641.00	4,641.00	4,641.00	6	0.0%	10.00
12/16/2020	WWSSUG	SG	2013	4,641.00	4,641.00	4,641.00	4,641.00	6	0.0%	10.00
12/17/2020	WWSSUG	NK	2013	4,648.00	4,648.00	4,648.00	4,648.00	7	0.0%	20.00
12/17/2020	WWSSUG	SG	2013	4,648.00	4,648.00	4,648.00	4,648.00	7	0.0%	29.40
12/18/2020	WWSSUG	NK	2013	4,655.00	4,655.00	4,655.00	4,655.00	7	0.0%	54.50
12/18/2020	WWSSUG	SG	2013	4,655.00	4,655.00	4,655.00	4,655.00	7	0.0%	80.90
12/21/2020	WWSSUG	NK	2013	4,573.00	4,573.00	4,573.00	4,573.00	82	1.0%	20.00
12/21/2020	WWSSUG	SG	2013	4,573.00	4,573.00	4,573.00	4,573.00	82	1.0%	15.50
12/24/2020	WWSSUG	NK	2013	4,593.00	4,593.00	4,593.00	4,593.00	6	0.0%	61.40
12/24/2020	WWSSUG	SG	2013	4,593.00	4,593.00	4,593.00	4,593.00	6	0.0%	15.00
12/25/2020	WWSSUG	NK	2013	4,601.00	4,601.00	4,601.00	4,601.00	8	0.0%	30.00
12/25/2020	WWSSUG	SG	2012	4,601.00	4,601.00	4,601.00	4,601.00	26	0.0%	28.40
12/25/2020	WWSSUG	SG	2013	4,601.00	4,601.00	4,601.00	4,601.00	8	0.0%	40.00

Figure 3.2 Sample of commodity dataset

3.2.2 Dataset Description

Machine learning needs data to learn and make the decision. If collected data have a different format it should be converted into machine understandable format. The data type of commodities attributes is explained in the table below.

Table 3.1dataset description

No.	Attribute name	Datatypes	Description of attributes
1	Trade Date	int64	Date on which commodity sold
2	Symbol	object	Special code assigned to commodities
3	Warehouse	object	The place where commodities stored
4	Production year	int64	The year in which commodities produced
5	Opening price	float64	The first price of the day
6	Closing price	float64	The last price of the day
7	High	float64	The highest price of the commodities of the day
8	Low	float64	The minimum price of the day
9	Change	float64	The difference between low and high
10	Percentage change	float64	The percentage of price change
11	Volume (Ton)	float64	Amount of sold commodity in tone.

3.3 Data Preparation

Data preparation is the method of converting raw data into a suitable format for preprocessing. Data analysts and scientists modify raw data before running it through a machine learning algorithm to produce predictions. Any raw data collected firsthand should be passed via preparation of data before being fed into the machine learning models. In this study, unstructured data that is collected from the Ethiopia commodity exchange is first prepared for preprocessing. The main purpose of data preparation is to make data understandable for further use in machine learning. There are different data preparation techniques in machine learning, and some of them are elaborated on below.

3.4 Data preprocessing

The quality of the data will directly affect the performance of the model. Data preprocessing is used to reduce noise, detect trends, and identify relationships before being fed into our model (Jha

& Sinha, 2013a). To get quality output, we have to feed preprocessed data to the proposed model. Data can be preprocessed using the scaling technique, normalization technique, or binarization technique depending on the data we need to feed into the proposed model. Unstructured data that was collected from the Ethiopian commodity exchange should be preprocessed before being used for training and testing.

3.4.1 Data cleaning

Data cleaning is the process of removing incorrect, corrupted, incorrectly formatted, and incomplete data within a dataset. It plays a significant role in model building. Some of the tasks of data cleaning are: -

- Removal of unwanted observations
- Fixing structural error
- Managing unwanted outlier
- Handling missing data
  - ✓ Dropping observations with missing values
  - ✓ Imputation

Using data cleaning techniques, the data was pre-cleaned before using it to reduce error and avoid duplicate data. NaN is the common feature which represent lost data in unclean dataset and the missing value is represented using mean, median and we fill the missing values with the same column to reduce the problem of missing value of the performance of predictive model. The cleaning of the dataset is used to improve the quality of training data which is used to enable accurate decision making and increase the performance of the predictive model.

3.4.2 Data Transformation

Transformation is the process of converting non-numerical data features into numeric formats. This is to prepare data for multiplication and the multiplication is easy for matrix form data. Matrix multiplication is possible only for numeric data types, and it should be transformed. The mechanism of converting the data into an appropriate format. This type of preprocessing technique is used in non-numerical attributes, which are not understandable by machines unless data is transformed. It is used to convert non-numerical data into a numerical format that is easily untreatable by the machine.

3.5 Attribute Selection Techniques

With the use of just necessary data and the elimination of irrelevant data, we can reduce the input variable to our model using the attribute selection procedure. The dataset collected from the real world has many attributes and redundant attributes, which might not play an equally important role in forecasting purposes. Selecting only important features from real-world data is difficult. So, feature selection is a technique for reducing input variables to reduce time complexity and improve model performance by using only relevant data and eliminating noise (Fite, 2021). It is the mechanism of reducing the number of input variables to reduce computational costs while developing a predictive model (Eseye et al., 2019). Feature selection in predictive models has the following advantages (Hajek & Michalak, 2013).

- ❖ Reduce training time: If only important features are selected, the complexity of the model is reduced, and training time is faster.
- ❖ Improves Accuracy: When the number of misleading data decreases the model accuracy increases.
- ❖ Reduce overfitting: Feature selection is used to reduce the number of misleading data or noise and this helps to reduce decision-based noise which is used to reduce the overfitting of the predictive model.

So, selecting appropriate features helps the predictive model to preforms well. There are different feature selection techniques in supervised learning. These are: -

Wrapper Methods: This is a feature selection strategy that uses univariate statistics to filter and select intrinsic attributes of features rather than cross-validation performance. The wrapper method of feature selection assesses the value of predictor subsets to a specific forecaster or classifier. Because numerous predictor sets are assessed by a predictive model or fitting method in each cycle, wrapper techniques show enhanced performance. (Eseye et al., 2019). The wrapper feature selection method often results in better predictive accuracy than filter methods. Some of Wrapper method type feature selection are Exhaustive feature selection, forward feature selection, backward elimination, and recursive feature selection.

Filter Methods: This feature selection method selects features based on the relevance of features and their correlation with dependent variables. Feature selection using the filter approach is independent of any prediction model and sorts features based on statistical properties (Eseye et al., 2019). This method is the fastest and best approach when the number of features is very large and is used to reduce overfitting. The filters used in the filter method of feature selection in supervised learning are information gain, chi-square test, correlation coefficient, Pearson correlation coefficient, variance threshold, and mean absolute difference. Among the different types of correlation coefficients, Pearson will be used to find the dependence between each attribute of the commodity dataset. The relation between each attribute is calculated and the ones related to each other are averaged together to find the average price of the day. Finally, each attribute's Pearson correlation was calculated to check whether they have a relationship or not. Therefore, the variable with a positive correlation coefficient is used in a price forecasting model using deep neural network techniques.

3.6 Modeling

Raw data were preprocessed, divided into training and testing sets, and then fed into our deep learning predictive models. For this study three deep learning neural networks like long short-term memory, Bidirectional long short-term memory, and the gated recurrent unit will be used. The criteria to select three neural networks for this study is, that neural network models can forecast future values depending on prior, sequential time series data. For this study, we have collected time series data from the Ethiopian commodity exchange and we selected three neural network algorithms explained below. After being evaluated with evaluation criteria outperforms the model selected as the commodity price forecasting model which is used to predict the future price of agricultural commodities mentioned above.

3.6.1 Long short-term memory (LSTM)

Long short-term memory is the well-known type of neural network which is used in time series analysis. It is highly helpful in forecasting commodity prices since it can store historical data. One type of recurrent neural network has the capability of catching data from past stages and using it for future predictions (Moghar & Hamiche, 2020). This is so because past prices are what determines how much a commodity will cost in the future. In forecasting situations involving long-term data, the application of the Long Short-Term Memory (LSTM) based on a "memory line" has proven to be highly helpful (Moghar & Hamiche, 2020). LSTM node consists of a set of cells responsible for storing passed data streams. There are three gates in LSTM:

- Forget Gate: produces the binary numbers 0 and 1, with 1 being used to display stored data and 0 being used to completely reject it.
- Memory Gate: This gate is responsible for choosing which information will be kept in the cell.
- Output Gate: is used to display the final result from the model.

The LSTM technique is preferred for problems involving sequential data or time series because of the aforementioned features.

3.6.2 Bidirectional long short-term memory (BLSTM)

Long-term memory that is bidirectional allows information to travel in both directions across neural networks. The forward and backward directions of information flow are known as the past to the future and the future to the past, respectively. This is carried out to safeguard both past and present data(Althelaya et al., 2018)(Wang et al., 2019). The information from both directions of the model in BILSTM is combined using a concatenation mechanism like average, multiplication, and sum them together to can produce a more meaningful output. The model can predict more accurately than typical LSTM-based models due to the training of additional data in BILSTM.

3.6.3 Gated recurrent unit (GRU)

This neural network has advantages over LSTM. GRU is quicker and requires less memory than LSTM, however, LSTM is more accurate when working with datasets that contain longer sequences. GRU, in contrast to LSTM, only transfers one hidden state between time steps. It is possible to hold both short-term and long-term dependents in this hidden condition. Two gates in GRU are used to selectively filter out unimportant data while keeping critical data: the update gate and the reset gate. The two gates have two values of 0 and 1, where 0 denotes that the input data or hidden state is insignificant and 1 denotes that the data is important and will be used in the future. These values are multiplied with the input data or hidden state.

After each of the above-discussed algorithms will be trained with three commodities dataset (Coffee, Sesame, and green mung beans) and tuned with hyperparameter tuning like learning rate, number of epochs, batch size, and dropout rate to find the optimal model to predict the future prices. Finally, the model with high performance and less loss function will be selected as the best model to forecast the price of the top three agricultural commodities that the Ethiopian commodity exchange has been working on.

3.7 Development Tools

There are hardware and software tools used for modeling and implementing this study. The hardware and software used in this study are explained below.

Hardware tools

The hardware that will be used for designing and implementing commodity price forecasting is mentioned in the following table according to their use. We will use many hardware tools to do this study, but try to explain a few of them as follows.

Table 3.2 Hardware Tools

No.	*Hardware tools name*	*Use of tools*
1.	RAM	Used to speed up the training process of our machine
2.	Hard disk	Used to store data inside the computer. Especially big dataset
3.	USB flash drive	Used to provide portable storage of big data
4.	GPU	Used as external memory and processes many pieces of data simultaneously to increase the computation for big dataset

Software tools

This is the software used for writing code and implementations. Different deep learning software tools will be used for modeling commodity price forecasting using deep learning. Some of the software used for this study is explained in the following table.

3.3 Software Tools

No.	Software Tools	Explanations
1.	Anaconda	- Anaconda is an open-source and free software tool used to develop a machine learning model. - Used to simplify the management of packages and deployments

		- Anaconda has the tools which easily collect data from different sources using machine learning and AI. - Anaconda is the industry standard for developing, training, and testing on a single machine. - Therefore, Anaconda is the software tool used for this study.
2.	Jupiter Notebook	- Jupiter notebook is the simplest editor which is easy to explore and plot the data. It is a user-friendly machine learning editor. - Allows real-time visualization.
3.	Edraw max	- This the design tools used to draw the proposed architecture of the price forecasting model. - Edraw max is the simplest drawing tool.
4	Tensor Flow	- It is an open-source library that is used to maximize the performance of numerical modeling and allows the developer to easily build and deploy machine learning applications.
5	Keras	- Keras is the software tool used to provide clear and correct feedback upon the error performed by the user. - Keras is a Python-based framework that makes debugging and exploration a breeze. - Highly modular neural networks library written in Python

3.8 Performance Evaluation Metrics

The concept of developing models works on the constructive feedback principle, in which the model is built and the feedback is obtained from evaluation metrics. The study builds a model that gets feedback from evaluation metrics, makes enhancements, and continues until it reaches the desired accuracy. The model performance is used to measure the divergence or relation of obtained result from the original one. Evaluation metrics are used to clearly understand the performance of the model (Ouyang et al., 2019). The performance evaluation metrics used in the regression algorithm are used for this study. It enables us to identify how well the model performs with less error. Some of the evaluation metrics used for commodity price forecasting using deep learning are explained below.

3.8.1 Root mean squared error (RMSE)

The root means the squared error is a measurement of the typical size of a mistake with the mean of the observations. It is normalized by the mean of the observed values (Bouktif et al., 2018). If the value of coefficient variation is high, it means that there is a high error range in the built model. It takes the average of the square of the difference between the actual values and the predicted values. According to (Bouktif et al., 2018), The equation of RMSE is given below.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N} (Predicted_i - Actual_i)^2}{N}}$$

Equation 3.1 Equation of Root mean squared error

Where N=Total number of observations

3.8.2 Mean Absolute Error

Mean absolute error is the evaluation metric of the model in which the difference between the predicted value and actual value is averaged. The mean value of the sum of absolute differences between actual and forecasted(Bouktif et al., 2018). The mean absolute error is calculated as follows: -

$$MAE = \frac{1}{N}(\sum_{i=1}^{N} |(Actual - predicted\ value)|)$$

Equation 3.2 Equation of mean Absolute Error

Where N is the total number of observations

3.8.3 Mean Squared error (MSE)

Mean squared error is a regression model evaluation metric that is used to measure how the predicted value and actual value are related or matched to each other. MSE is also known as mean squared deviation (MSD). The performance of the model increases as the value of the MSE approach approaches zero. When the value of MSE is zero, the actual value and the forecasted value are similar, indicating that the model properly predicted it. The equation of MSE is given below. N is the total number of observations.

$$MSE = \frac{1}{N}(\sum_{i=1}^{N}(Actual - predicted\ value))2$$

Equation 3.3 Equation of Mean Squared error

One of the main advantages of MSE is the graph of mean square error is differentiable and used as a loss function in evaluating the performance of the predictive model.

3.8.4 Correlation Coefficient (CC)

The correlation coefficient is the statistical measure of the strength of the relationship between the relative movements of two variables. It is the correlation between the predicted value and actual values(Gashaw, 2019). For this study among many types of the correlation coefficient, we will use the Pearson correlation coefficient which is used to measure the degree of relationship between linearly associated variables. The formula is given below. In the equation below, **Xi** is observation, **Yi** is predicted,**n** is the number of data, **x̄** & **ȳ** **mean** of actual and predicted.

$$r_{xy} = \frac{n\sum x_i y_i - \sum x_i \sum y_i}{\sqrt{n\sum x_i^2 - (\sum x_i)^2}\ \sqrt{n\sum y_i^2 - (\sum y_i)^2}}$$

Equation 3.4 Pearson's Correlation coefficient formula

If the obtained number of the correlation coefficient is high (1), show that the actual value and predicted value are highly correlated and the model is more accurate and if the value is 0, there is no correlation between them and the model is less accurate.

CHAPTER FOUR

4 DESIGNING OF PROPOSED SOLUTION

4.1 Overview

In the previous topic, the research methodologies, procedures, and tools used to develop commodity price forecasting using deep learning were elaborated. To solve the problem mentioned in the introduction part of this study, to answer a raised research question, and to fill the shortcoming of the paper mentioned in the literature review, the proposed solution of the model was used to create the link between methodology and implementation. The main aim of this section is to describe in detail the architecture of commodity price forecasting using deep learning techniques. The section not only focuses on the design of architecture but also describes the procedure and steps that are followed to achieve the implementation of the proposed model.

4.2 The architecture of proposed commodity price forecasting

The main aim of this study was to build an automated commodity price forecasting model using an artificial neural network sub-part of a deep neural network and find out future the price of commodities like sesame, coffee, and green mung bean in the following years to provide market information for farmers, traders, and governments. The proposed architecture of this study will be used as the guidelines for the implementation. The step by steps used to reach the final result of this study is clearly shown in the proposed architecture of this system with general representation. In the proposed solution design, the three-algorithm used to implement this problem are shown in general form and their detailed representation is elaborated in the research methodology of this study in the previous chapter. Since machine learning is data-driven, the first task was to collect data from the Ethiopian commodity exchange. After data collection, the preprocessing of collected data takes place to make raw data ready for machine learning. The preprocessed data were classified into training datasets and testing datasets. Data preprocessing tasks used in this study include noise removal, dimension reduction, and normalization. The next step to data preprocessing is the building of predictive neural network models using artificial neural networks like long short-term memory (LSTM), bi-directional long short-term memory (BILSTM), and gated recurrent units (GRU) is carried out by tuning the training of each model with hyperparameter tuning. After a model is built and evaluated using evaluation metrics, the best model with high accuracy and low loss function is used as the final predictive model of the commodity price forecaster. The proposed architecture of commodity price forecasting using deep learning techniques is shown in figure 4.1 below. This proposed model of commodity price forecasting using the deep learning technique is shown below.

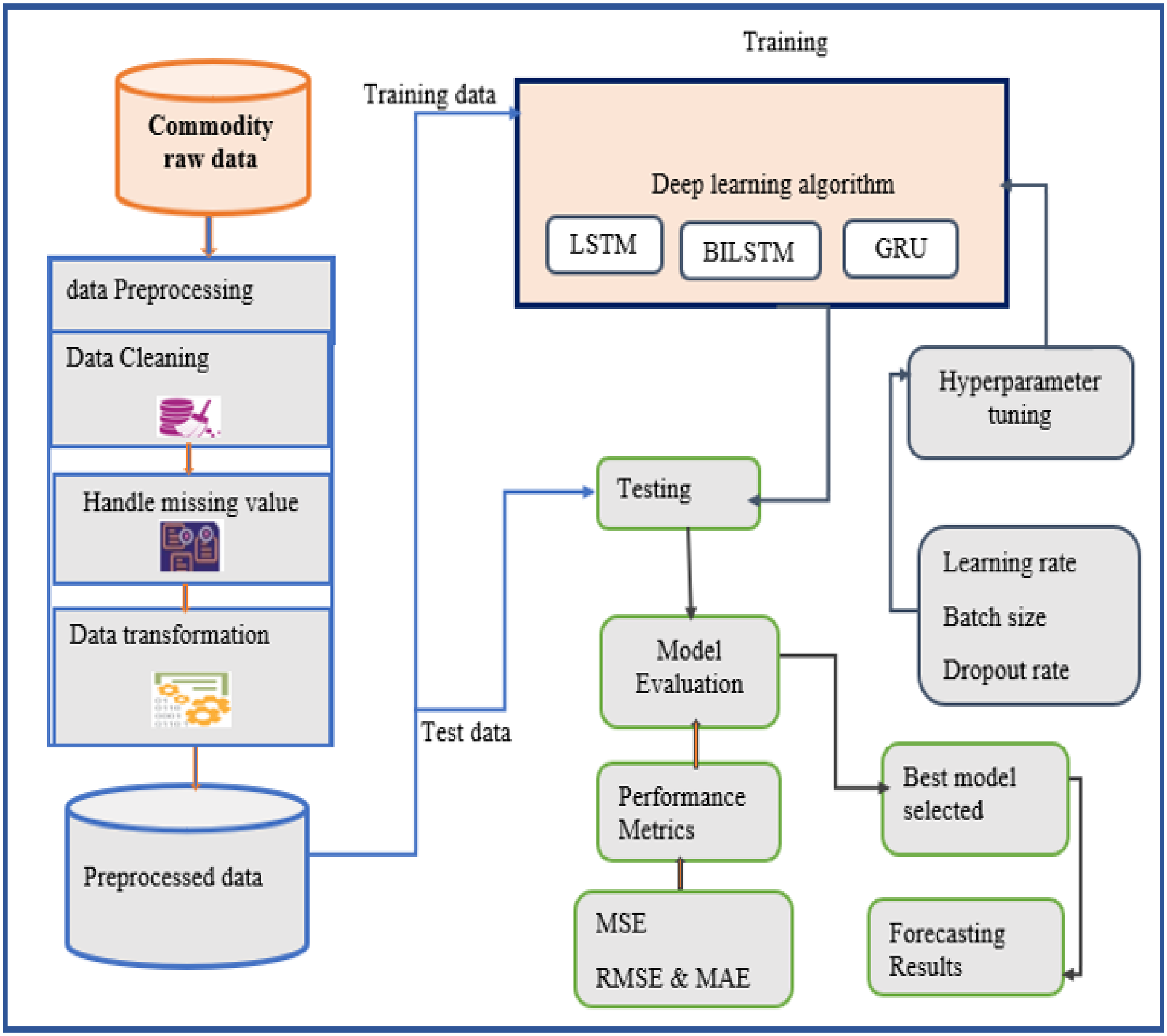


Figure 4.1 The proposed architecture of Commodity price forecasting

4.3 Data Preprocessing Algorithms

Real data collected from various sources contain varying amounts of unnecessary noise, which has an impact on the overall performance of the commodity price predictive model. In the preprocessing step, missing values are removed or replaced with averages of the rest. The raw data should be organized into different data types and normalized. Data with different data types should be converted to a machine-understandable format. Following that, the prepared data should be converted to comma-separated value (CSV) format and saved as an a.csv file. CSV files are easily parsed by a Python parser to be used further in model building. No numerical features of commodities, such as commodity code or warehouse name, are handled because they contribute nothing to model building, and only continuous data of commodities, such as low price, high price, close price, and high price, are used for model building. The main task of preprocessing is to make data ready to be fed to a machine. It contributes a prominent role in the performance of our model. Row data should pass via this step before being used in model building the architecture of data preprocessing is shown in diagram 4.2 below.

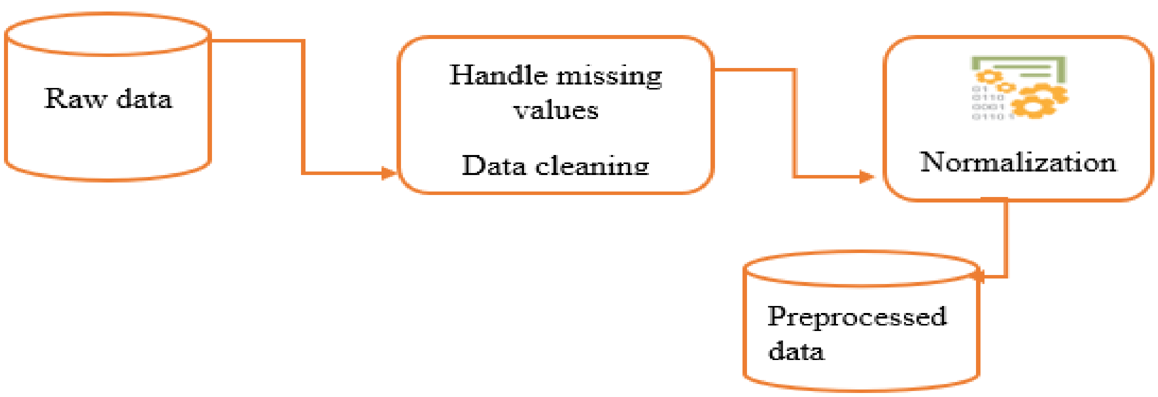


Figure 4.2 Data preprocessing steps

4.4 Hyperparameter optimization

The term hyperparameter has the prefix ''Hyper'' which explains the top-level parameter that controls the performance of the model and learning processes. Hyperparameter optimization is used to optimize the performance of machine learning(Smithson et al., 2016). Hyperparameter is known as external to the model. Because the value of the hyperparameter is set before the training of the model starts. [2]Hyperparameters are any parameters whose configuration and values have been predetermined and are still in effect after training. The hyperparameter setting is used to select

[2] https://towardsdatascience.com/parameters-and-hyperparameters-aa609601a9ac

the best model or optimal architecture among the given model(Zheng et al., 2019). When a created model is configured properly, it performs well for a given dataset (Zheng et al., 2019). Those hyperparameters tuned in artificial neural networks are the number of neurons, batch size, learning rate, activation function, optimizers, dropout rate, and the number of epochs used for training the model. It is used to extract the highest performance out of the models.

The optimization of the model performance depends on the values of the hyperparameters explained above. The optimal value of those parameters which enables our model to perform better is obtained at the end and used as the final value of the predictive model for commodity price forecasting using deep learning techniques.

4.5 Model evaluation method

The process of developing a recommended solution finally comes to a close with the examination of the proposed deep learning model. It is a method of assessing a learning model's performance, as well as its strengths and weaknesses, through the use of several evaluation indicators.[3] One of the challenging problems in regression is using accuracy terms in model evaluation. Since accuracy is the term used to elaborate on all the predictions made how many of the predictions were accurate and matched with the actual value. Unlike in classification problems, in regression the target variable is continuous, and if the model is evaluated based on accuracy parameters the final model phase the problem of overfitting. This method was applied to a dataset to check whether the built model was properly trained or not on the given dataset.

To evaluate the performance of the model, Regression model evaluation metrics like root means square error (RMSE), mean absolute error (MSE), and MAE are used to find the minimum error between forecasted and actual values of the trained dataset. The model with the low value of error is said to be a well-performed model. Another model evaluation metric of commodity price forecasting using a deep learning technique is using of the loss function. The loss function is used to compare target and predicted output values. As loss function decrease the performance of the model increase. Instead of K fold cross validation early stopping with the number of epochs applied to find at what iteration our model performs better and stop the extra iteration after the critical point on which the highest accuracy is recorded.

[3] https://www.enjoyalgorithms.com/blog/evaluation-metrics-regression-models

CHAPTER FIVE

5 EXPERIMENT AND IMPLEMENTATION

5.1 Overview

In the previous chapter of commodity price forecasting using deep learning, the architecture of the proposed system was elaborated. This chapter is all about the implementation of the designed model in the previous chapter. This section starts by arranging the model development environment setup, data preprocessing, model building, testing, and evaluation of the developed model. To make a clear understanding important portion of the code is displayed in the form of a code snippet.

5.2 Working Environment

The working environment is a subpart of the result and discussion which elaborates the environment setup of the hardware used during the implementation of this model with their description. It describes the hardware used to execute RNN and LSTM. These working environments are:

- Desktop: The desktop is used for building and training commodity price forecasting using deep learning algorithms like LSTM and RNN.
  - Operating system: Windows 10 pro
  - System Type: 64-bit operating system, x64-based processor
  - Processor: Intel(R) Core (TM) i5-4590 CPU @ 3.30GHz 3.30 GHz
  - Memory size: 12.0 GB
  - Pen and Touch: No pen or touch input is available for this display
  - Model: DELL OptiPlex 7020
- Laptop: Personal computer used for writing documents and few codes.
  - Model: 3168NGW
  - Operating System: Windows 10 pro
  - Memory size:4.00 GB
  - System Type: 64-bit operating system, x64-based processor

5.3 Deployment Environment Setup

To implement commodity price forecasting using a deep learning algorithm different IDEs and programming tools have been used.

5.3.1 Programing Language and their libraries used

Python is a free and open-source programming language with rich libraries that have been used for this model development.

- **Python 3.9.7:** is used to build this model. This version of python has many packages and libraries that play a prominent role in systematic computation.
- **TensorFlow 2.8.0:** Is used to provide API that is used to build and train the model
- **Keras 2.8.0:** The most user-friendly python library which runs on top of the TensorFlow library used to make the implantation of neural networks easy. This library underpins the backend neural organize computation.

5.3.2 Integrated Development Environments (IDE)

IDE used to edit python programming code to build the predictive model are:

- **Jupyter Notebook:** This is a python built-in editor to write python code. Jupyter notebook get popularity due to easily exploring data and plotting results easily. It has the following advantage over editors:
  - ✓ Easily showcasing the work
  - ✓ Jupyter notebook is easy to host server side which is important for security resolves.

For this model development, the Jupyter notebook was used to obtain the above features.

- **Colab:** Known as 'Collaboratory'.IS IDE allows to write and execute python code through the browser and most of the time suited for data analysis. To execute deep learning online for free and to access GPU, this IDE is used in this model building.
- **Microsoft Excel 2016:** This editor is used to prepare data before loading it to pandas' library. Raw data collected from the Ethiopian commodity exchange was first inserted into

this editor and saved with the '.CSV' extension for the next preprocessing in the python notebook.

5.4 Commodity Price forecasting Implementation

5.4.1 Data preprocessing implementation

As explained in the research methodology, The first step in machine learning implementation is data preprocessing that transforming input data before training a neural network. Data should be preprocessed before being fed into the model to reduce error output. The implementation of data preprocessing of commodity price forecasting includes handling missing values, normalization, and feature selection. To preprocess data, first data should be loaded from a file using the panadas library of python and converted loaded data to the data frame. For this study, the data collected was saved in CSV extension and we directly load as follows.

```
#Laoding of commodity dataset for preprocesing
import pandas as pd
data=pd.read_csv('E:/Dataset/commodity_3.csv')
```

Code snippet 5.1 load dataset saved with CSV extension

5.4.2 Implementation of Feature Scaling (Normalization)

This step of implementation is used to transform data in different range features into the same range between 0 and 1. This method is applied only to the column with numeric values in the commodity dataset. In LSTM and RNN if training data is normalized, the model reduces the neural network from weighting feature inequalities. This study used MinMaxScaler () library from sklearn to transform the given dataset.

```
#Import library to perform preprocesing and MinMax Scaler
from sklearn import preprocessing
from sklearn.preprocessing import MinMaxScaler
sc_minmax=preprocessing.MinMaxScaler(feature_range=(0,1))
data_norm=sc_minmax.fit_transform(data)
```

Code snippet 5.2 Normalizing data using MinMaxScaler

5.5 Pearson Correlation implementation

The test statistic known as Pearson's correlation coefficient is used to assess the statistical association or relationship between two continuous variables. It is the technique of measuring the association between attributes of interests to include or exclude features based on the value of correlation. One sub-branch of the filter method is the Pearson correlation we used to filter the attributes. The sample code is given below.

```
import matplotlib as mpl
import matplotlib.pyplot as plt
corr=data.corr()
rcp = mpl.rcParams
fig = plt.figure(figsize=(10,8))
sns.heatmap(data.corr(),annot=True,cmap='Blues',
vmin=-1,vmax=1,linewidth=1,linecolor='gray',square=True,cbar=False)
```

Figure 5.1 Pearson Correlation Implementation

5.6 Model Implementation

The first task of model implementation started with preprocessing and was followed by attribute selection. After data is preprocessed and important features selected, in this case, the average price of a commodity selected and the splitting of the data into training and test data is carried out with 20% and 80% respectively. Then the training data is fed into the three deep learning algorithms LSTM, GRU, and BILSTM. To implement the predictive model, we have to import important libraries from sci-kit, TensorFlow, Keras, and math. Those libraries are used to call during training models, testing, and evaluation of predictive models. The library loaded from Keras is used to train neural network models, and the library imported from TensorFlow also plays a great role in large datasets to provide high performance in predictive models. In addition to TensorFlow and Keras, we imported a math library to display graphical and static data for better visualization. Once the following libraries are imported, they will be used throughout the implementation simply by calling them. Some of the important libraries used for the building of this model (using long short-term memory, Gate recurrent unit, and Bidirectional long short-term memory) are imported using the following sample snippet code.

```
#Laoding of important library for implment commodity price forecasting
import pandas_datareader as web
import pandas as pd
import numpy as np
import seaborn as sns
import statistics as sts
from matplotlib import pyplot as plt
from matplotlib import rcParams
import matplotlib.pyplot as plt
from numpy import array
from sklearn.compose import ColumnTransformer
from sklearn.datasets import fetch_openml
from sklearn.impute import SimpleImputer
from sklearn.preprocessing import MinMaxScaler
from sklearn.metrics import mean_squared_error
from sklearn.preprocessing import LabelEncoder
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense
from tensorflow.keras.layers import LSTM
import tensorflow as tf
import math
from google.colab import files
import io
```

Code snippet 5.3 loading of the important library for LSTM implementation

Among the deep learning algorithm used for this study, long short-term memory (LSTM) is trained on three datasets by separating the dataset into two parts for training and testing dataset. The division of the dataset is by (80%,20%) and (70%,30%) for training and testing respectively. Finally, the division with the highest accuracy was selected. To implement LSTM, some modules of Keras were used. One of the Keras libraries used was Sequential which was used to initialize the neural network and dense was used to connect the neural network layers and display the final results. The dropout module is added after LSTM is added to the layers to prevent the overfitting of the model. The value of dropout, learning rate, number of epochs, and batch size is changed iteratively five times to find the optimal result. This is shown under hyperparameter tuning. In the implementation of commodity price forecasting using LSTM, the return sequence used is true to show the last output and input shape to show the shape of training data.

The sample code used to build long short-term memory is depicted in the code snippet below.

```
model=Sequential()
model.add(LSTM(256,return_sequences=True,input_shape=(1000,1)))
model.add(LSTM(128,return_sequences=True))
model.add(Dropout(0.1))
model.add(LSTM(64))
model.add(Dense(1,activation='relu'))
opt = tf.keras.optimizers.Adam(learning_rate=0.005)
model.compile(loss='MSE',optimizer = opt)
```

Code snippet 5.4 Code snippet to create the LSTM model

model.add (LSTM (256, return sequences=True, input_shape= (1000,1))) in code snippet 5.1 shows the LSTM layers where 256 represent number of hidden units with return sequence true to show the existence of final output of the model. To prevent overfitting in the LSTM model we used a dropout of 10% and the Relu activation function which helps the model to learn complex patterns in the data was used in the model building above. Relu activation function is used for linear regression or time series problems. For optimization purposes, the Adam optimizer which is better than other optimizers by having faster computation time was used in developing the LSTM model.

The second algorithm is bidirectional long short-term memory implementation which is almost similar to LSTM model building with few differences. In Bidirectional LSTM both forward and backward are used in information flows. BLSTM model has the capability of combining both forward and backward output using concatenation, sum, and multiplication operations. The information from both directions is combined to produce a more meaningful full output when we use the bidirectional long short-term memory. The sample snippet code to build BLSTM is below.

```
# define LSTM
model = Sequential()
model.add(Bidirectional(LSTM(128, return_sequences=True), input_shape=(time_step, 1)))
model.add(TimeDistributed(Dense(1, activation='relu')))
model.add(Dropout(0.4))
opt = tf.keras.optimizers.Adam(learning_rate=0.002)
model.compile(loss='mean_squared_error',optimizer=opt)
```

Code snippet 5.5 Sample code to build Bidirectional LSTM model

As shown in the above sample code of the BILSTM model, the model. add (Bidirectional (LSTM (128, return sequence=True)) is used to add a bidirectional neural network. The training and testing splitting size for BILSTM is similar in size to LSTM as mentioned above.

The next is the third proposed deep learning algorithm for this study. As mentioned in the research methodology, the gated recurrent unit is the neural network with less memory and is more accurate in long sequence times series data. The implementation of this model is shown below with a sample code snippet as follows.

```
#The Gated recurrent model building sample code
model= Sequential()
model.add(GRU(units=100, return_sequences=True, input_shape=(x_train.shape[1],1), activation='relu'))
model.add(Dropout(0.5))
model.add(GRU(units=25, activation='relu'))
opt = tf.keras.optimizers.Adam(learning_rate=0.001)
model.add(Dropout(0.5))
model.add(Dense(units=1))
```

```
model.compile(loss='mean_squared_error',optimizer=opt)
```

Code snippet 5.6 Sample code to build GRU model

In GRU model building, to reduce overfitting, we used the dropout after each layer. The impact of each hyperparameter in developing the model is clearly explained in hyper parameter tuning of this study.

5.7 Hyperparameter Tunning implementation

Hyperparameter tuning is an important technique in deep learning model building and neural networks to increase the performance of the model(Zheng et al., 2019). IF hyperparameters are not properly tuned, the model might take lots of time to train, the unnecessary number of epochs may be used and the overperformance of the model is reduced due to a mismatch of hyperparameter tuning. These hyperparameters to be tuned in neural networks are the number of epochs, activation function, batch size, optimizers, number of layers, and learning rate of the model. Three deep neural networks (LSTM, GRU and BLSTM) used in commodity price forecasting for sesame, green mung bean and coffee are depicted in the table below using five iterations. The table show the number of trial and the result of each hyperparameter tunning on three different datasets.

Table 5.1 Hyperparameter tuning in LSTM for Green mung bean

Trial	Used Hyperparameters for green mung bean using LSTM					
	Epochs	**Batch size**	**Learning rate**	**Dropout**	**Accuracy**	**Validation Accuracy**
1.	256	**128**	**0.001**	**0.5**	**99.95**	**99.81**
2.	**128**	**64**	**0.002**	**0.4**	**99.95**	**98.81**
3.	**64**	**32**	**0.003**	**0.3**	**99.99**	**96.34**
4.	**32**	**16**	**0.004**	**0.2**	**99.95**	**97.37**
5	**100**	**64**	**0.005**	**0.1**	**99.95**	**97.63**

Table 5.2 Hyperparameter tuning in LSTM for Sesame

Trial	Used Hyperparameters for Sesame using LSTM					
	Epochs	**Batch size**	**Learning rate**	**Dropout**	**Accuracy**	**Validation Accuracy**
1.	256	**128**	**0.001**	**0.5**	**99.93**	**99.95**
2.	**128**	**64**	**0.002**	**0.4**	**99.92**	**99.6**
3.	**64**	**32**	**0.003**	**0.3**	**99.92**	**99.8**
4.	**32**	**16**	**0.004**	**0.2**	**99.76**	**98.6**
5	**100**	**64**	**0.005**	**0.1**	**99.9**	**99.48**

Table 5.3 Hyperparameter tuning in LSTM for Coffee

Trial	Used Hyperparameters for Coffee using LSTM					
	Epochs	**Batch size**	**Learning rate**	**Dropout**	**Accuracy**	**Validation Accuracy**
1.	256	**128**	**0.001**	**0.5**	**99.82**	**92.84**
2.	**128**	**64**	**0.002**	**0.4**	**99.85**	**94.36**
3.	**64**	**32**	**0.003**	**0.3**	**99.8**	**95.08**
4.	**32**	**16**	**0.004**	**0.2**	**99.64**	**95.02**
5	**100**	**64**	**0.005**	**0.1**	**99.89**	**97.03**

Table 5.4 Hyperparameter tuning in GRU for Green Mung bean

Trial	**Used Hyperparameters for Green mung bean using GRU**					
	Epochs	**Batch size**	**Learning rate**	**Dropout**	**Accuracy**	**Validation Accuracy**
1.	256	**128**	**0.001**	**0.5**	**99.99**	**93.41**
2.	**128**	**64**	**0.002**	**0.4**	**99.99**	**93.21**
3.	**64**	**32**	**0.03**	**0.3**	**99.94**	**93.55**
4.	**32**	**16**	**0.04**	**0.2**	**99.98**	**93.89**
5	**100**	**64**	**0.005**	**0.1**	**99.99**	**93.33**

Table 5.5 Hyperparameter tuning in GRU for Sesame

Trial	**Used Hyperparameters for Sesame using GRU**					
	Epochs	**Batch size**	**Learning rate**	**Dropout**	**Accuracy**	**Validation Accuracy**
1.	256	**128**	**0.001**	**0.5**	**99.98**	**88.66**
2.	**128**	**64**	**0.002**	**0.4**	**99.99**	**88.41**
3.	**64**	**32**	**0.03**	**0.3**	**99.99**	**87.94**
4.	**32**	**16**	**0.04**	**0.2**	**99.99**	**87.71**
5	**100**	**64**	**0.005**	**0.1**	**99.99**	**88.66**

Table 5.6 Hyperparameter tuning in GRU for Coffee

Trial	Used Hyperparameters for Coffee using GRU					
	Epochs	**Batch size**	**Learning rate**	**Dropout**	**Accuracy**	**Validation Accuracy**
1.	256	**128**	**0.001**	**0.5**	**99.61**	**99.93**
2.	**128**	**64**	**0.002**	**0.4**	**99.97**	**99.81**
3.	**64**	**32**	**0.03**	**0.3**	**99.75**	**99.98**
4.	**32**	**16**	**0.04**	**0.2**	**99.88**	**99.89**
5	**100**	**64**	**0.005**	**0.1**	**99.93**	**99.97**

Table 5.7 Hyperparameter tuning in BILTSM for Green mung bean

Trial	Used Hyperparameters for Green Mung bean using BLSTM					
	Epochs	**Batch size**	**Learning rate**	**Dropou t**	**Accuracy**	**Validation Accuracy**
1.	256	**128**	**0.001**	**0.5**	**99.54**	**91.27**
2.	**128**	**64**	**0.002**	**0.4**	**99.1**	**87.86**
3.	**64**	**32**	**0.03**	**0.3**	**99.62**	**94.09**
4.	**32**	**16**	**0.04**	**0.2**	**99.1**	**87.68**
5	**100**	**64**	**Adam**	**0.005**	**0.1**	**99.93**

Table 5.8 Hyperparameter tuning in BILTSM for Sesame

Trial	Used Hyperparameters for Sesame using BILSTM					
	Epochs	**Batch size**	**Learning rate**	**Dropout**	**Accuracy**	**Validation Accuracy**
1.	256	**128**	**0.001**	**0.5**	**99.73**	**85.51**
2.	**128**	**64**	**0.002**	**0.4**	**99.44**	**82.56**
3.	**64**	**32**	**0.003**	**0.3**	**99.98**	**93.4**
4.	**100**	**128**	**0.004**	**0.2**	**99.44**	**82.56**
5	**100**	**64**	**0.005**	**0.01**	**99.44**	**82.56**

Table 5.9 Table 5 Hyperparameter tuning in BILTSM for Coffee

Trial	Used Hyperparameters for Coffee using BILSTM					
	Epochs	**Batch size**	**Learning rate**	**Dropout**	**Accuracy**	**Validation Accuracy**
1.	256	**128**	**0.001**	**0.5**	**95.12**	**96.24**
2.	**128**	**64**	**0.002**	**0.4**	**96.17**	**97.72**
3.	**64**	**32**	**0.03**	**0.3**	**97.04**	**98.47**
4.	**32**	**16**	**0.04**	**0.2**	**97.86**	**99.82**
5	**100**	**64**	**0.005**	**0.1**	**98.98**	**99.8**

The above table demonstrates the effect of each hyperparameter tuning on the accuracy of training and validation data. For each of the three deep learning, neural network adam was used as an optimizer and rectified linear activation (RLU) which is a linear, simple, fast activation function used for implementation. To compare the performance of our study, we used three deep learning algorithms: long short-term memory, gated recurrent units, and bidirectional long short-term memory. In each of these algorithms, the number of implemented hyperparameters was the same in the number of iterations, and the models were trained on a different dataset. This hyperparameter setting enables us to choose the optimal model for our predictive model(Zheng et al., 2019). After five types of hyperparameters (learning rate, dropout rate, batch size, number of epochs, and optimizers which is adam for regression algorithm), the compilation of the deep learning model is performed. Adam optimizer is used for optimization because adam is an adaptive moment optimization algorithm that works with changing learning rates. In hyperparameter tuning, a high dropout rate and the low learning rate is to make the neural network converge slowly to a high accuracy rate or optimal values. The compiled model should run to see the final output of each of the mentioned hyperparameter tuning listed in the table above. For each of iteration, 80% of the dataset was used for training the model while 20% of the dataset was used for validation purposes or testing. The splitting of dataset by 70% of the for training and 30% of the dataset is excluded due to low results after evaluated.

CHAPTER SIX

6 RESULTS AND DISCUSSION

6.1 Overview

This chapter is all about the elaboration of results obtained in the previous implementation part of this study. The experimental results of commodity price forecasting are discussed with tangible evidence obtained from the implementation of the model. Results and discussions focus on three main parts of this study. In the first part, the result of data preprocessing is discussed while in the second part the result obtained from the model building were explained. In the third part, the performance of the built model is evaluated using different metrics, and the results obtained as best are elaborated. Finally, the general concept of this study is discussed to make sure the raised research question in the introduction part gets an answer or not and whether the gap identified in the literature review was solved or not, is explained in this section.

6.2 Dataset Correlation Result Analysis

The dataset for commodity price forecasting has twelve independent features, with one dependent feature, which is used in the forecasting price of each commodity. The correlation result analysis is used to measure the relationship between two variables to reveal the interdependence between them. The value of the correlation coefficient lays somewhere between 1 and -1. If the value of the correlation approaches zero, the two variables are less related, and if the value of the correlation is near one, the two variables are highly related. The direction of the association is described by the sign of the correlation coefficient. To find the correlation between two variables, we used Equation 3.5, mentioned in the research methodology of this study. There are three levels or intervals of correlation results obtained from this analysis. These are zero correlation, positive correlation, and negative correlation results.

Zero Correlation: This show that there is no relation between the variables. This correlation is excluded from the graph below.

Positive correlation: The two variables are highly correlated if the value of the correlation between them is positive. According to the result obtained from the correlation opening price, close price, high, low, and average price of the commodity have highly correlated values as mentioned in table 6.1 of the heatmap of the Pearson correlation between each variable.

Negative correlation: This correlation shows that the two variables are independently proportional if one variable value increases the other variable's value decreases. Negatively correlated variables are excluded from the graph below using the Vmax and vmin of Pearson correlation. The value of the correlation result is given in the correlation table below.

Table 6.1 Correlation Table

	PY	OP	CP	H	L	Av	Ch	Vo
PY	1.000000	0.885843	0.862293	0.885473	0.886181	0.884282	-0.141518	-0.051042
OP	0.885843	1.000000	0.973487	0.999970	0.999977	0.998252	-0.071425	-0.047744
CP	0.862293	0.973487	1.000000	0.973530	0.973447	0.985292	-0.209591	-0.038377
H	0.885473	0.999970	0.973530	1.000000	0.999947	0.998256	-0.071423	-0.046427
L	0.886181	0.999977	0.973447	0.999947	1.000000	0.998236	-0.071377	-0.048877
Av	0.884282	0.998252	0.985292	0.998256	0.998236	1.000000	-0.107407	-0.045526
Ch	-0.141518	-0.071425	-0.209591	-0.071423	-0.071377	-0.107407	1.000000	-0.056647
Vo	-0.051042	-0.047744	-0.038377	-0.046427	-0.048877	-0.045526	-0.056647	1.000000

The Pearson correlation coefficient result of above table is shown using heatmap below.

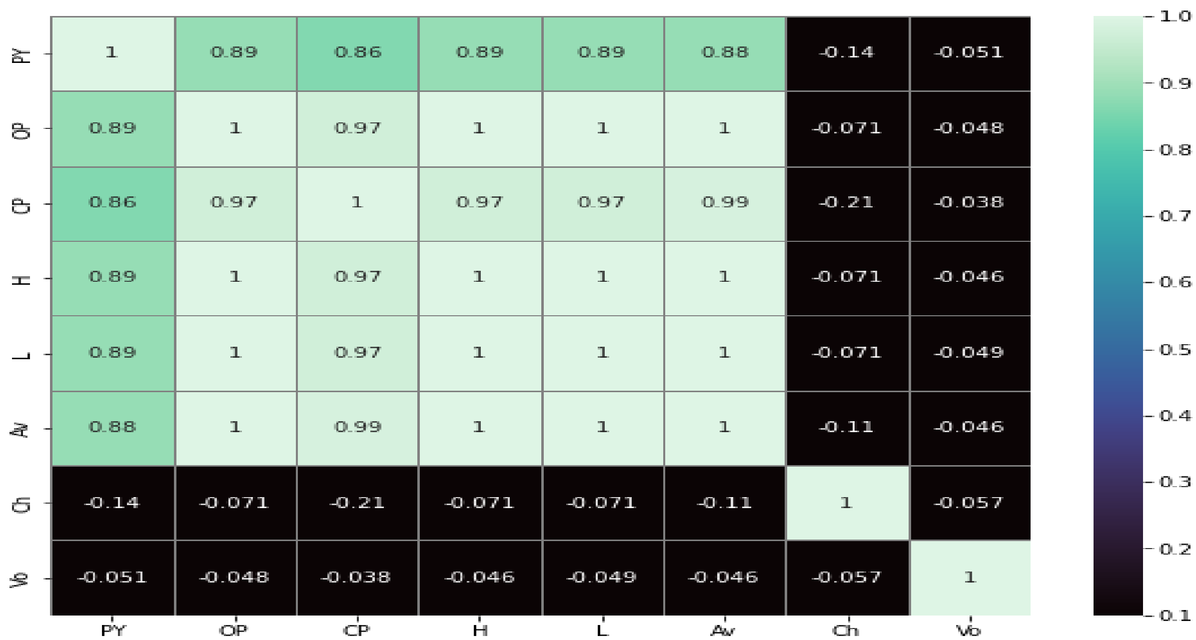


Figure 6.1 Data correlation analysis result of sesame

As observed above from Pearson correlation the feature with the highest or positive correlation coefficient value is used in commodity price forecasting. In three commodities (Coffee, green mung bean, and Sesame) the value of the correlation coefficient is positive for the close price, open price, high, low, and the average is positive and those features are used for forecasting purposes. The value of the correlation coefficient was used for the feature selection method because we used the feature with the highest correlation coefficient. This correlation coefficient result of coffee also positively correlated with close price, high price, low price, the average price of the day, and opening price of the day as shown in the figure below like in sesame mentioned above.

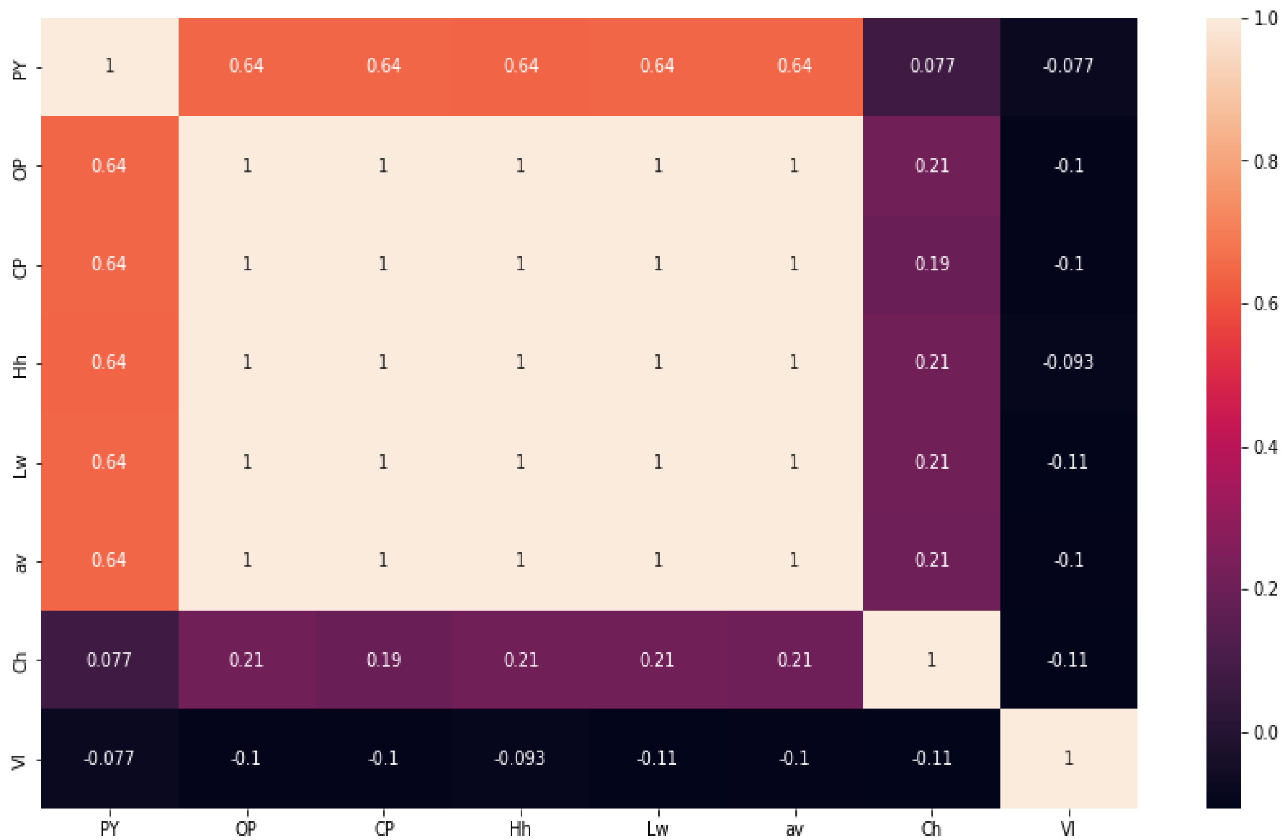


Figure 6.2 Data correlation analysis result of Coffee

The attribute with a low correlation coefficient value below 0.95 is excluded and not used as the feature which contributes to the price forecasting in the two best models selected (long short-term memory and Gated recurrent units) based on their performance as mentioned in the hyper tuning part of this study.

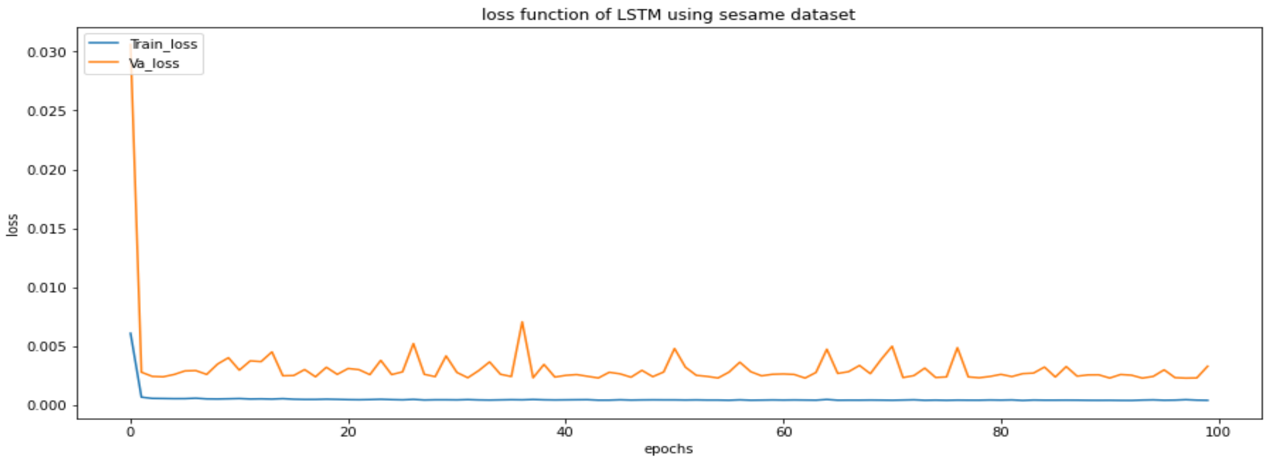
6.3 Model Evaluation Result

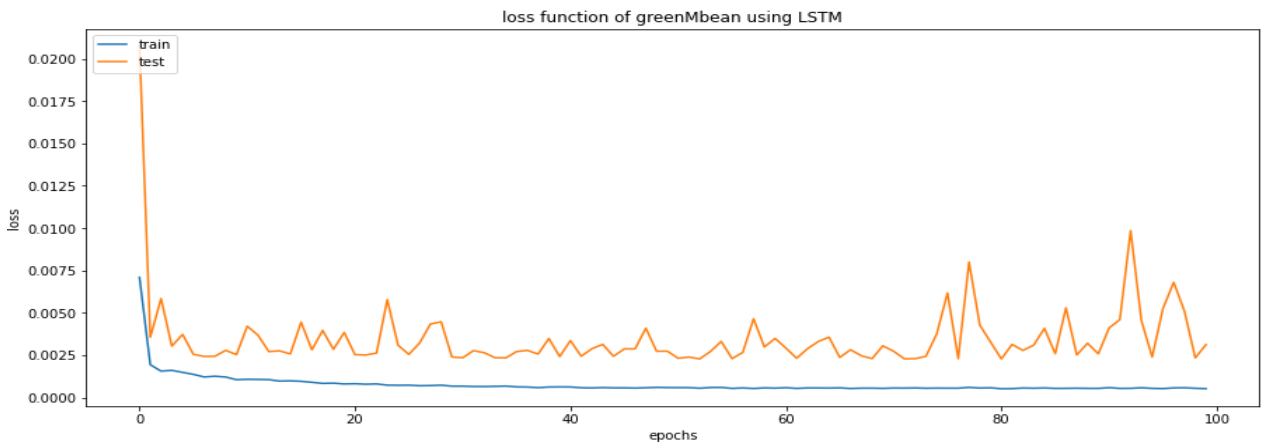
The experiments of this study were focused on three deep-learning networks, and the best two models were selected based on the performance of each model as mentioned under the hyperparameter tuning. The model was evaluated under different hyperparameters and the one with a small loss function was selected as the best model for forecasting the price of commodities in the case of the Ethiopia commodity exchange. According to the hyperparameter tuning results, long short-term memory outperforms other models with an accuracy of 99.93%, while gated recurrent units come in second with an accuracy of 99.9%, with little difference in accuracy with LSTM. These two outperform models were evaluated with regression evaluation metrics like mean squared error, mean absolute error, and root mean squared error, and the results obtained using each evaluation metric are tabulated in table 6.3 and table 6.4 below. The average RMSE of long short-term memory using sesame was 317.7 and the MSE of the same commodity using LSTM was 100935.65. The MAE was 216.85 and the. The overall result obtained using the long-short term for each of the agricultural commodities is explained in the table below.

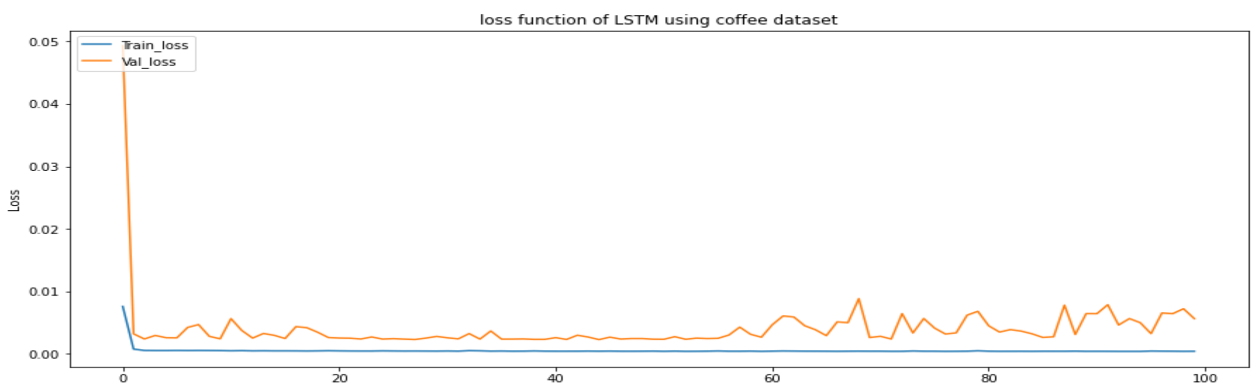
Table 6.2 LSTM model Evaluation analysis

Metrics	Using LSTM model		
	Commodity types		
	Sesame	Green _Mung_beans	Coffee
RMSE	104.57	42.154	116.5
MSE	10935.65	1777.11	13572.25
MAE	216.85	108.66	715.98
Loss	0.016	0.0039	0.0025

The loss function is used to show the difference between the outcome of the forecasted and actual value of the model. Loss functions serve as a gauge of how well our model can forecast the desired result. The model with high accuracy has a low loss function. The loss function of commodity price forecasting using the deep learning technique (LSTM) is depicted in the figure below. As shown in the diagram, the value of the loss function decreases as the number of epochs increases. In the graph below the blue color is used to show the loss function of training data while the yellow color is used to show the value of the loss function after training or validation loss function of the long short-term memory model for forecasting the prices.







Based on the model's performance with various settings of the hyperparameters, the Gated recurrent neural network, which excels in sequence learning by overcoming the issues with long- and short-term memory vanishing gradient and exploding gradient (Shen et al., 2018) was chosen as the second-best model. On three agricultural commodities, the average accuracy obtained using GRU was 99.8% with a minimal loss function. The regression evaluation metrics MSE, RMSE, and MAE, which are listed in Table 6.3 below with the corresponding values obtained using each of them, were also used to assess this model's performance.

The assessment metrics for neural networks with gated recurrent units had a very modest value that was below zero. This demonstrates that the model operates efficiently with little error. The result obtained after experimentation on three of the commodities show a low value of error relative to the dataset size used for training and validation. Especially the loss function value of the model decreased; which shows the increase in accuracy. Table 6.4 of the examination of the GRU model evaluation metrics explains this outcome.

Table 6.3 GRU model Evaluation analysis

Metrics	Using GRU model		
	Commodity types		
	Sesame	Green _Mung_beans	Coffee
RMSE	376.044	207.045	733.4
MSE	141409.08	42887.63	537875.56
MAE	1289.22	2024.03	499.24
Loss	0.0029	0.0071	0.0039

The loss function is one parameter that shows the performance of the predictive model. The loss function value of the three model decreases and reach the final value mentioned in table 6.3 above.

6.4 Hyperparameter Tuning result analysis

The main aim of hyperparameter tuning is to find the optimal combination of parameters used to minimize the loss function in the regression algorithm and providing of better results. The hyperparameter tuning used in Gated recurrent unit (GRU), BILSTM and long short-term memory (LSTM) are the number of epochs, learning rate, batch size, optimizers, and dropout rates. The result obtained by using the value of each parameter was shown in table 5.1, table 5.2, table 5.3, table 5.4, table 5.5, and table 5.6. As shown in the table, among the given model long short-term memory outperforms the Bidirectional long short term and GRU. The average accuracy and average validation accuracy obtained after each iteration of hyperparameter tuning are shown in the table below.

Table 6.4 The result of hyperparameter tuning analysis

Type of Commodities		Coffee, Sesame, and Green Mung beans
Models	Average Accuracy	Average Validation Accuracy
LSTM	99.93	99.89
GRU	99.8	93.83
BILSTM	98.68	91.64

The result of hyperparameter tuning in each commodity showed that LSTM accuracy was 99.93% and validation accuracy of 99.88%. The accuracy shown in table 6.2 shows the training accuracy of the model, while the validation accuracy shows the validation accuracy after training the model. According to the results obtained from the model, 99.8% training accuracy and 93.89% validation accuracy. When the model is developed without using hyperparameters (the model is not properly tuned), the accuracy of the model is less than when using hyperparameter tuning, which means the average training accuracy of the LSTM model is 92.67%, and the validation accuracy of 90.78%. In GRU, the training accuracy of the gated recurrent unit was 88.87 % and the validation accuracy obtained without using the hyperparameter tuning was 90.65%. This shows that the use of hyperparameters is used to increase the accuracy of both training and validation while the loss function of the model inversely decreases. The accuracy obtained from using hyperparameter tuning using long short-term memory and gated recurrent units is shown in the bar graph below. This hyperparameter tuning was applied to three agricultural commodities like coffee, sesame, and green mung beans in each of the three deep learning algorithms. The average accuracy and validation accuracy of the model obtained after using selected hyperparameter tuning are shown below.

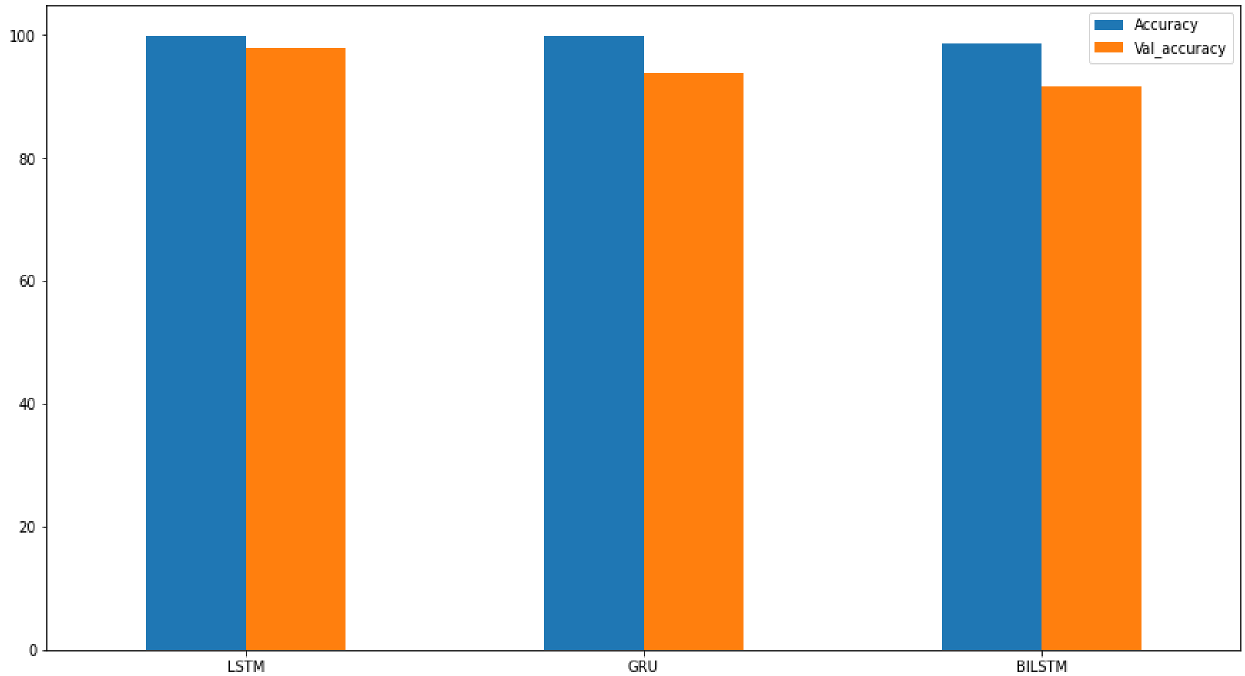


Figure 6.3 Hyperparameter Tuning result analysis

As depicted in figure 6.5 above, the accuracy of the two deep learning models (long short-term memory and gated recurrent units) is almost similar with little difference. The validation accuracy of the gated recurrent unit is less than the accuracy of the training data. The output of the hyperparameter tuning shows that our model neither overfits nor under its. This is because the validation accuracy of the model and the training accuracy is close to each other. In LSTM, the training accuracy is 99.93% and 99.88%, which is close to each other, and the model is free of underfitting and overfitting. The value of validation and training in GRU is little varied from each other; there is high variation in training accuracy and validation accuracy, which shows that the model has encountered underfitting problems with few errors as compared to LSTM not selected as the best model.

6.5 Comparison of models

There are many studies conducted regarding the price forecasting domain to increase the productivity of crops and increase the profit our country gets from foreign markets by exporting those commodities to foreign markets. Price prediction is used to guess the price of goods in the future based on historical data. As a result, the deep learning price forecasting technique was used in this study to forecast the future price of goods to increase farm income and study the problem that exists in the goods market to help farmers make better and more informed decisions about prices and production. To solve the problem of price prediction, some studies were conducted using machine learning and deep learning techniques by different researchers and were included in the literature reviews of this study as related works. The main aim of comparing this study with the previously conducted price forecasting related study mentioned in the related work of this study was to check whether this research outperforms the existing study or not.

In (Amin, 2020), predicted the price of a daily commodity using a machine learning algorithm like a support vector machine (SVM) for only short-term prediction, and the study mentioned that the ensemble model outperformed another model. But the forecasting is only for daily and does not depend on long-time lookback or historical data to forecast the long-time price in the future. The author obtained an accuracy of 99% after hyperparameter tuning to his model but used a small dataset. The author used MSE, MAE, and R2 model evaluation methods to evaluate the predictive model that he developed. However, since the author used a small dataset and forecasted only for one day, it is difficult to predict for the long term, like a week or month, using his model. In addition to this, using small-sized datasets has problems in developing an efficient model. The obtained result has low performance and cannot properly predict the price as needed in the future. This problem was solved in this study using a commodity price forecasting deep learning technique by using long-term and gated recurrent neural networks. Another author (Vijh et al., 2020) tried to forecast the closing price of the stock using machine learning techniques. The author used two machine learning algorithms, artificial neural networks, and random forest techniques, to forecast the next day's closing price of the stock The author compared two models, ANN, and random forest, and obtained that ANN outperformed based on evaluation metrics of MSE and RMSE. The researcher used regression models evaluation techniques like RMSE, MSE, and R2 and selected the ones with low values of errors. MAPE (0.77%) and RMSE (0.42) were obtained with low values and show that the models are efficient in forecasting future one-day stock prices. The study's shortcomings were the small dataset size and the use of only one financial parameter, the closing price, without taking into account high, low, and volume of trade. In our study, those financial parameters were included, and the accuracy of the model outperformed the previous models. Another author (Tziridis et al., 2017) used machine learning techniques to predict the price of air tickets. The author used a dataset of size 1814 to predict the price of air tickets. Machine learning was used in two ways in his study: for regression to predict the price of airline tickets and for classification purposes. The first regression machine learning was used to predict the exact price of an air ticket while the next one was used to provide the decision on whether to buy the ticket at that price or not. After many algorithms were compared, the researcher obtained that the Bagging regression tree outperformed the multilayer perceptron, generalized regression neural network, extreme learning, and regression SVM with an accuracy of 88%. But the author used only the Thessaloniki to Stuttgart airfare dataset. The accuracy of the model is not good. The proposed model outperforms the previous model with an accuracy of 99.9% and used enough datasets from different types of commodities. In (Gebisa, 2019), the author used machine learning techniques to predict the closing price of coffee and obtained an accuracy of 92%. The author used linear regression algorithms like SVM, Decision Tree, KNN, and LSTM and among linear regression, SVM was outperformed on only one parameter of financial data, which was the closing price of the coffee. Even if the mentioned goods have many features like opening price, low price of the day, and adjacent closing price of the day, only one parameter or feature was included for prediction purposes in the model. According to the study, the price of a three-year market direction was predicted with ARIMA, which is a classical algorithm. But the author selected LSTM as the best model to predict the price of coffee on a single feature. But our proposed model included four highly correlated parameters by averaging and obtained an accuracy of 99.9 % using long-term memory This proposed study of commodity price forecasting was compared with different studies conducted regarding price forecasting using machine learning or deep learning techniques.

6.6 Discussion

One of the ten-year economic growth plans for 2021–2030 prioritizes agriculture because it is the mainstay of Ethiopia's economy (Teddy Tefera, n.d.). About 80-85% of the people in Ethiopia are farmers, and the country's government is focusing on this industry. The Ethiopian government's economic development plan seeks to create an efficient connection between farmers and commodity markets as well as the commercial value chain. This effective linkage is carried out through the Ethiopian commodity exchange, a marketplace where buyers and sellers meet to exchange commodities. It is working on commodities like coffee, sesame, and green mung beans. This study focuses on implementing neural network techniques to forecast commodity prices. Predicting a product's future price, help us to know whether it will go down in the future, figuring out when a farmer will sell their harvest based on price figure, and predicting the future price of each commodity are the primary challenges in commodity price prediction. This problem was solved using deep learning methods that forecast the future using past time series data.

Raw data collected from data from the Ethiopian commodity exchange needs to go through several processing procedures, such as preprocessing, noise removal, and data transformation before being fed into the machine. The correlation coefficient method was utilized to comprehend which characteristic to use in model creation and the dependence between features used to identify their importance. The Pearson correlation is used to find the relation between two features, and the feature with the positive Pearson value is selected for building the commodity price forecasting model. Those features which had positive Pearson values were high, low, open price, and the average price of the day. In this study, three deep learning neural networks were used to conduct experiments, and the one with a low loss function and high accuracy was selected as the best model for forecasting purposes. The three deep learning neural networks used to compare their results were long short-term memory (LSTM), bidirectional long short term (BLTSM), and gated recurrent units (GRU). The performance of the three algorithms was compared after each model was tuned with hyperparameters. The parameters used for tuning the model were learning rate, number of epochs, optimizers, batch size, and dropout rate. The results of each parameter are shown in tables (5.1 to table 5.9) of the implementation part of this study. The performance of the developed model was evaluated with regression algorithm evaluation metrics like MSE, RMSE, and MAE. According to the results obtained, long short-term memory outperforms other models with an accuracy of 99.9% and a very low loss function. Therefore, LSTM based model will be used to solve the problem of price forecasting. The developed model of commodity price forecasting using LSTM can predict the price of three export commodities for the next years. The sample of the forecasted and actual average price of Commodities is depicted in the table below.

Table 6.5 Actual and forecasted price of the commodity

Trade date	Sesame		Green mung beans		Coffee	
	Average (Actual)	Forecasted price	Average (Actual)	Forecasted price	Average (Actual)	Forecasted price
2020-06-01	5746.0	5623.162	8180	8239.660	3465.00	2950.20703
2020-06-01	5746.0	5711.8725	8632	8610.392	1793.00	2103.26586
2020-06-01	5593.0	5609.2143	8129	8244.409	2597.25	2231.50927
2020-06-01	5262.0	5339.1782	8186	8264.998	1728.00	1712.00805
2020-06-01	5450.0	5383.7436	8186	8252.933	1879.00	1945.25634
2020-06-01	5450.0	5500.3798	8186	8235.868	2383.50	2274.24096
2020-06-01	5572.0	5567.2504	8638	8417.710	2465.00	2509.27319
2020-06-01	5598.0	5590.0195	8638	8451.543	2737.50	2812.04126
2020-06-01	5598.0	5595.5527	8638	8476.948	3020.00	2990.42724
2020-06-01	5266.0	5292.4316	9089	8999.808	2901.00	3086.53588
2020-06-01	5266.0	5331.6337	8186	8374.997	3288.00	3269.03564
2020-06-01	5454.0	5440.1054	8638	8535.698	3222.00	3336.30908
2020-06-01	5454.0	5545.7050	9089	8963.704	3347.00	3215.37304
2020-06-01	5454.0	5555.8847	8191	8240.559	3206.00	3429.98779
2020-06-01	5576.0	5537.3676	8191	8302.945	3344.00	3259.46411
…….	…….	…….	…….	…….	…….	…….
2021-12-17	7242	7283.9248	8643	8551.2128	1793.00	1952.23779
2021-12-17	7495	746.5957	8643	8579.4716	2597.25	2377.30981
2021-12-17	7495	7425.0449	8643	8598.5068	1728.00	2069.32543
2021-12-17	7495	746.2104	8191	8213.1318	1879.00	1900.61450
2021-12-17	7495	7452.7622	8643	8571.2646	2383.50	2089.6782
2021-12-17	7665	7620.7373	8197	8389.3828	2865.00	2907.19140

Table 6.6 above, shows the sample of forecasted prices and the average price of three commodities. The model forecasted commodity prices based on six years' time series of historical data. The sample of forecasting result which is machined in table above is shown in below figure using time line graph. The following graph show the Actual or average daily price of commodity on Y axis and the trade date of the commodity on X axis.

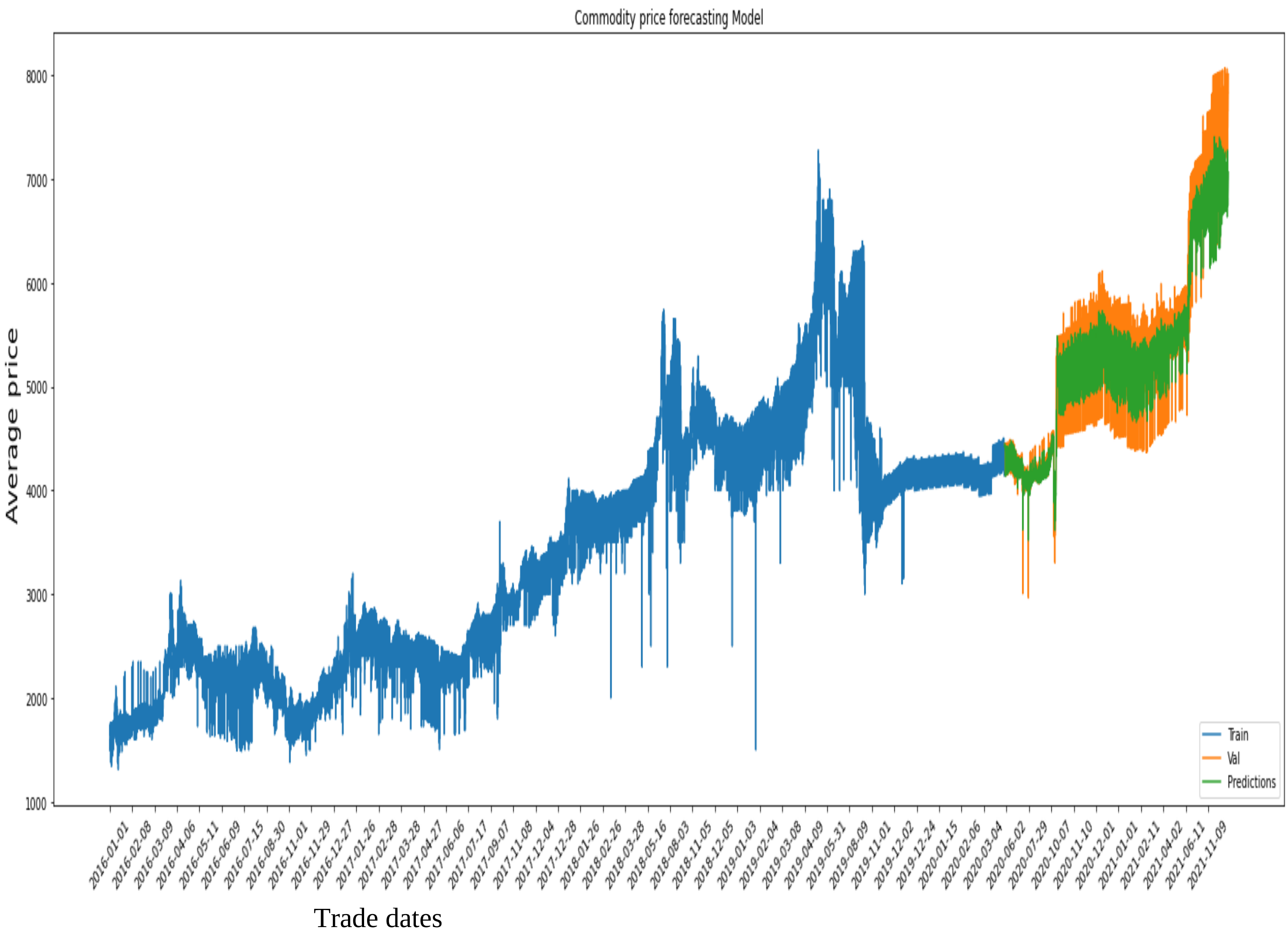


Figure 6.4 Commodity Price forecasting dataset distribution result

The primary goal of this model is to forecast for the upcoming years after checking for the actual and forecasted pricing indicated above. Therefore, the price of the commodities for the following three years will be forecast based on the developed model. Once the model is trained on historical data, the model is saved and used to forecast the future price. The amount of historical data and the size of the lookback period used to create the model determine the forecasting year's duration. Because the model's effectiveness declines as the number of forecasting years increases, we used historical data spanning six years to make predictions for the next three years.

In order to increase the performance of the model, the selection of only important attributes of the data were selected. When all categorical values and continuous values used together without selecting the appropriate features, the performance of our model decrease due to some features are not related with target values. The selection of which feature more important is done using the relation between each attributes using Pearson correlation values.

In this study, hyperparameter tuning is used to control the performance of the predictive model. One of the hyperparameters used is dropout rate, which is added to the two layers of the predictive model. This is to the input layer and hidden layer only. We cannot use the dropout rate in the output layer because its dropout unit to avoid output in the output layer. As the size of the dropout rate slowly decreases and increasing of learning rate the accuracy of the model increases because it allowed the model to learn faster to sub-optimal final weight as shown under hyperparameter tuning. The lower learning rate increases the risk of overfitting. The too high dropout rate decreases the convergence rate of the model and it affects the final performance of the model. To optimize the model, we used adam optimizer which is adaptive to variable learning rates and RELU is a linear activation function used for this study because it is used to reduce the vanishing gradient. The varied rate of hyperparameters tuned in this study was used to optimize the performance of the predictive model and finally, an optimal model to forecast the price of the commodity in the next three years was developed. The model predicts the price starting from September 2022 to September 2025 for sequential trading dates. Six-year historical data was used to train the model that can predict for three years. The sample of the forecasted price of three commodities in the next years is shown in the table below.

Table 6.6 Sample of the forecasted average price of the three commodities

Sample of The Forecasted average price of the three commodities			
Trade date	**Sesame**	**Green Mung beans**	**Coffee**
2022-09-01	7861.11166769	7545.45827699	4919.833008
2022-09-02	7913.28341997	7558.84258926	4913.017090
2022-09-03	7959.92688042	7572.470417	4984.431641
2022-09-04	8037.67478865	7586.33939302	5083.004395
2022-09-05	7992.03004259	7600.45803148	4968.740234
2022-09-06	8159.58329237	7614.82916844	5019.620605
2022-09-07	8015.26812905	7629.45469528	4963.768555
2022-09-08	8270.33034295	7644.33508486	4951.538086
2022-09-09	8275.28088784	7659.47459275	5098.069336
2022-09-10	8180.53593504	7674.87038189	4916.074707
2022-09-11	8136.39453959	7690.52245229	4936.389648
2022-09-12	8293.04027444	7706.42702121	5007.395020
2022-09-13	8250.58426386	7738.97852355	4948.152344
2022-09-14	8289.08806199	7789.51652539	5001.508789
2022-09-15	8298.58217353	7772.46010935	4936.955078
2022-09-16	8299.07858247	7755.6093803	4915.441895
2022-09-17	8190.57619935	7824.15941519	4827.319336
2022-09-18	8153.06249547	7722.58219725	4865.504395
2022-09-19	8216.5249421	7806.75829613	4941.703125
2022-09-20	8380.94392908	7841.68914771	4960.903809
2022-09-21	8346.29984623	7859.307302	5046.465820
2022-09-22	8312.57199395	7876.96281093	4931.279785
2022-09-23	8379.73585951	7894.58758503	4987.416992
2022-09-24	8367.76910913	7912.07523447	4939.018066
2022-09-25	8416.65049845	7929.26120967	5011.429199
2022-09-26	8486.35170168	7945.85944021	4888.253906
2022-09-27	6456.8482061	7961.35358083	4926.545898
2022-09-28	8428.12040156	7974.8352989601	5082.483887
2022-09-29	8400.13941753	7984.73759055	4900.920898
2022-09-30	8472.88292021	7988.87591815	4918.940918
……..	…	….	…..

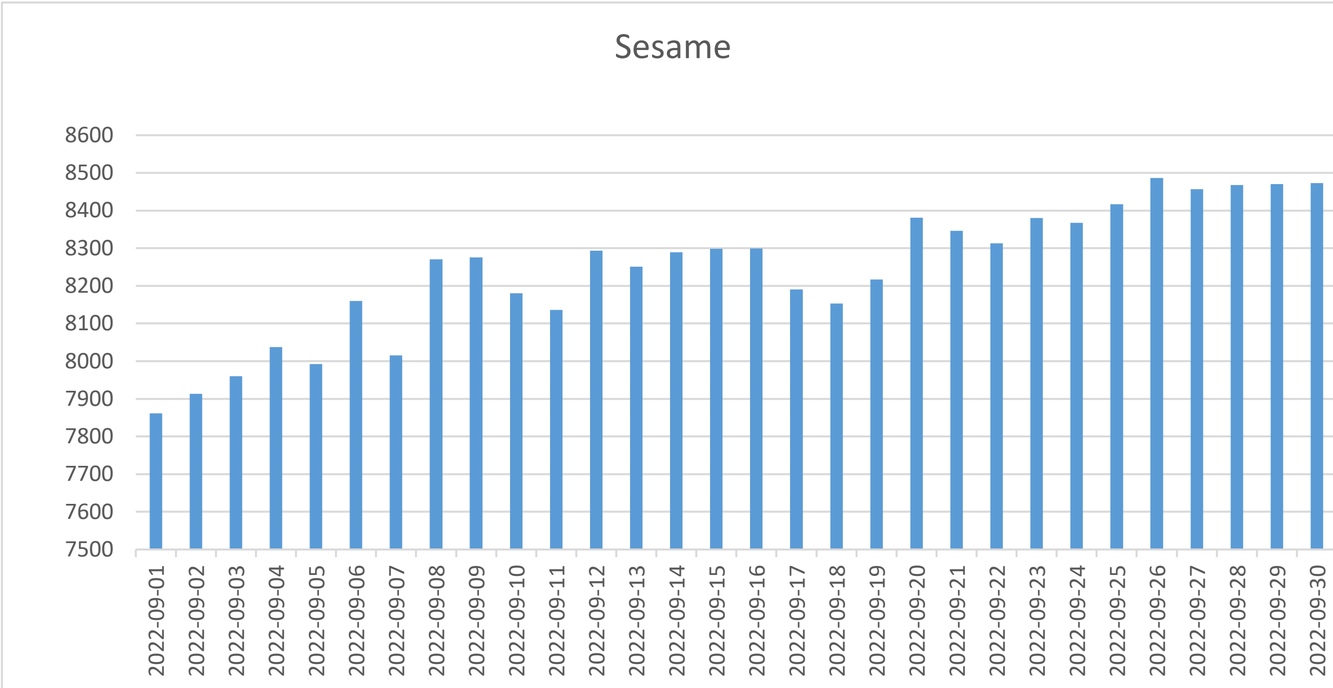


Figure 6.5 Sample of forecasted price of sesame

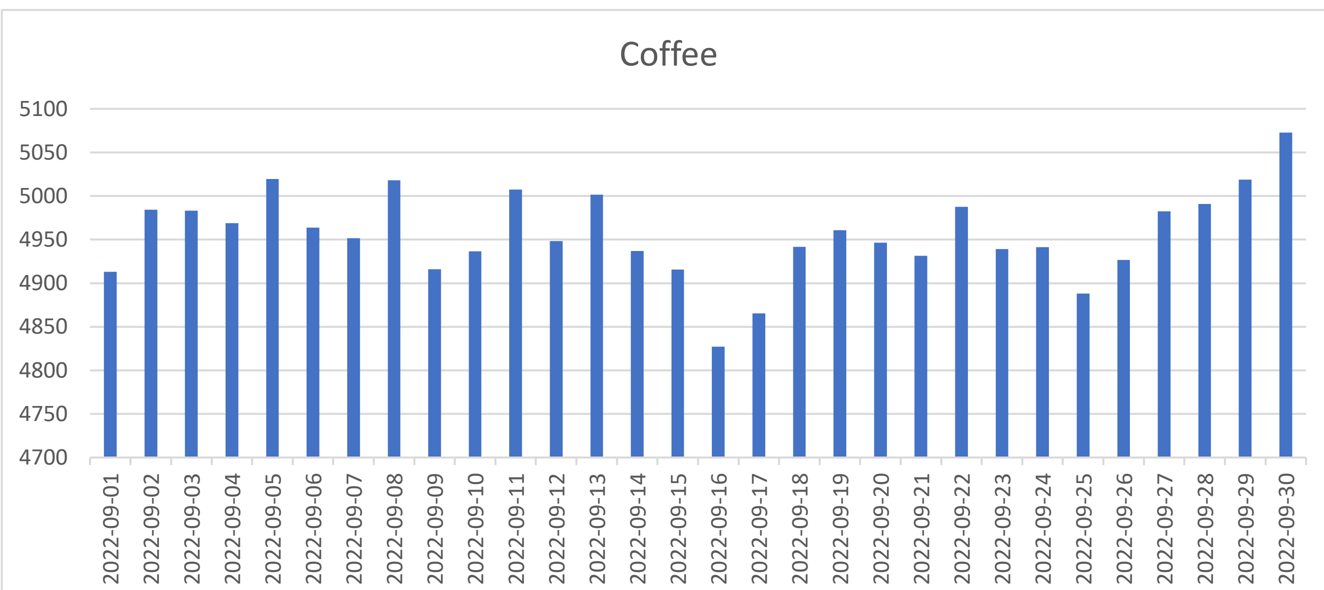


Figure 6.6 Sample of forecasted price of Coffee

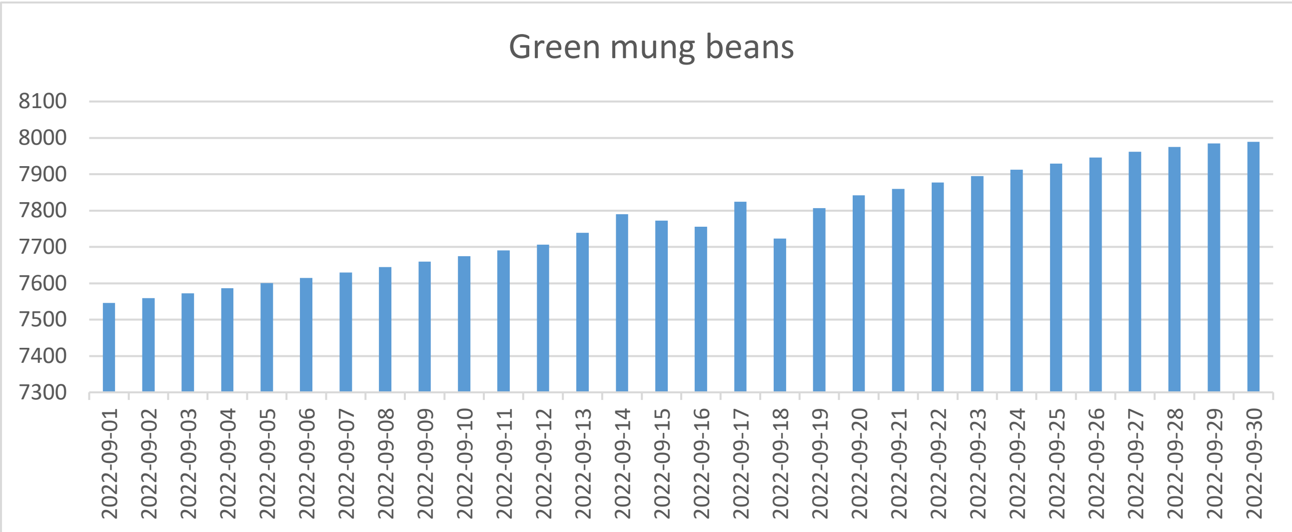


Figure 6.7 Sample of forecasted price of green mung beans

6.7 Contribution of this study

Even though there were studies conducted before this study regarding price forecasting, this study provided the following contributions.

- This study forecasts the price for the long term in a year unlike the previously conducted study and used to provide information on expected prices of commodity.
- The performance of the existing model on price forecasting is increased up to 6.7%.
- By choosing only the crucial features and eliminating the unimportant ones, we employed feature selection techniques to improve the recurrent neural network's performance to predict the future prices.
- Training the model on three different types of datasets allows us to get the advantage of evaluating the model and learning more.
- Long-term forecasting is used by governments and organizations to allocate their budget and plan for anticipated expenses for an upcoming period.
- This model can be used in the forecasting of other financial prices, like stock prices because trained on different datasets.
- This study can be used as a baseline for anyone who wants to go further in forecasting the prices of other agricultural commodities like wheat, sorghum, and in the stock market.

CHAPTER SEVEN

7 CONCLUSIONS AND RECOMMENDATIONS

7.1 Overview

This chapter offers the study's findings, recommendations, and plans for further research. This section recommends the general findings and limitations of the study mentioned in this chapter, as well as what other researchers can include improving the accuracy of this model. This section summarizes the performed tasks and provides the future direction.

7.2 Conclusion

Different agricultural strategies were introduced to increase the productivity of commodities by the Ethiopian governments (Teddy Tefera, n.d.). One of the strategies was to create a linkage between the market and producers. This linkage is created by ECX. The organization provides market price information for farmers and traders. This is possible by forecasting the future market direction of commodities. The main aim of this study was to forecast the price of agricultural commodities using deep learning neural network techniques. To achieve the goal of this study, the three top exported agricultural commodities (coffee, sesame, and green mung beans) data were collected from the Ethiopian commodity exchange. We have used a data set with 12 attributes for each of the commodities and the number of rows sesame contains was (24952,12), Coffee (68560,12), and green mung beans (3115,12) data were used to conduct this study. That data underwent a way of preprocessing to make it ready for the deep learning algorithm.

In this study, deep neural network models like long short term, bidirectional long short term, and gated recurrent units (GRU) were used to implement the model. The models compared with each other using hyperparameter tuning, and finally, long short-term memory (LSTM) outperformed the other models with small loss functions and high accuracy. The performance of the model was compared with the previously developed model as mentioned in table 6.5, and the proposed commodity price forecasting using deep learning techniques outperformed the previously built model with an accuracy of 99.9%. So, Ethiopia's commodity exchange would use the result of this study to inform the farmers and stakeholders to know the price of commodities in the future.

7.3 Recommendations and Future Work

The main aim of this study is to predict the future price of an export agricultural commodity by using deep learning techniques to simplify the problem of pre-guessing the future price of cash commodities to enhance agricultural productivity. We recommend that the agricultural sector and financial institutions use the result of the machine learning method to forecast future prices rather than use the classical method. This study's results can be used for the agricultural sector and mainly for the Ethiopian commodity exchange, which works on exporting those agricultural commodities. One of the responsibilities of ECX is to provide the market price information for commodity producers and traders; So, this is used to simplify their task to give the current price information and future price information for their customers. In Ethiopia, to develop a machine learning or deep learning model to forecast the price of commodities, no organized data can be used to conduct studies, especially for other commodities like teff, maize, lentils, and others. Not only is the unavailability of data, but the existing data is also not tabulated with important features that build the best model. The data we used to conduct this study even did not include features of commodities like factors affecting price, temperature, war, and international market impact. Therefore, it is better if those features are included and new technology is applied to predict future market directions for the rest of the commodities like maize, teff, sorghum, and wheat, which are highly demanded by the Ethiopian people.

Even though this study contributes its role in the prediction of agricultural commodity prices, we recommend another researcher to include how to handle non-trade dates, include factors affecting prices, and commodity grading, including decision-making capability whether the user buys or not buys, sells or not sells commodities in the future.

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Adama, Ethiopia

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Appendix A: sample of Coffee dataset

Trade Date	Symbol	Warehous	Productio	Opening F	Closing Pr	High	Low	average	Change	Persetnta	Volume (Ton)
2016-06-01	WYCBUGn	DL	2008	1180	1180	1180	1180	1180	15	1.00%	10.2
2016-06-01	WTP3	BG	2008	1320	1320	1320	1320	1320	20	1.00%	36.01
2016-06-01	WSDDQ1	HW	2008	1600	1605	1605	1600	1602.5	15	0.00%	14.4
2016-06-01	WSDAUGr	HW	2008	1200	1200	1200	1200	1200	0	0.00%	5.1
2016-06-01	WSDA5	HW	2008	1300	1300	1300	1300	1300	0	0.00%	7.21
2016-06-01	WGJQ2	HW	2008	1600	1600	1600	1600	1600	0	0.00%	3.6
2016-06-01	UYCB5	D1	2007	760	760	760	760	760	20	2.00%	8.36
2016-06-01	UYCB5	DL	2008	830	830	830	830	830	21	2.00%	34.48
2016-06-01	UYCB5	Dt	2008	830	830	830	830	830	20	2.00%	5.44
2016-06-01	UYCAQ1	DL	2008	2000	1950	2000	1950	1975	50	2.00%	21.28
2016-06-01	UYCA4	DL	2008	880	880	880	880	880	10	1.00%	5.1
2016-06-01	USUSDBU(	HW	2008	750	750	750	750	750	0	0	18.94
2016-06-01	USDCQ1	WS	2008	1095	1095	1095	1095	1095	25	2.00%	2.55
2016-06-01	USDA4	HW	2008	885	885	885	885	885	0	0.00%	15.66
2016-06-01	USDA3	HW	2008	930	930	930	930	930	5	0.00%	26.64
2016-06-01	ULK5	GM	2008	835	835	835	835	835	0	0.00%	53.55
2016-06-01	ULK5	Gt	2008	835	835	835	835	835	0	0.00%	15.3
2016-06-01	ULK4	GM	2008	870	870	870	870	870	0	0.00%	33.15
2016-06-01	ULK3	GM	2008	850	880	880	850	865	0	0.00%	51
2016-06-01	ULK3	Gt	2008	880	880	880	880	880	0	0.00%	12.75

Appendix B: Sample of Green mung beans dataset

Trade Date	Symbol	Warehous	Productio	Opening F	Closing Pr	High	Low	Average	Change	Persetnta	Volume (Ton)
2016-07-14	GMBS3	SG	2008	1650	1650	1650	1650	1650	0	0	20
2017-01-05	GMBSLG	SG	2009	1980	1980	1980	1980	1980	0	0	42
2017-01-05	GMBS3	SG	2009	2010	2010	2010	2010	2010	0	0	94.8
2017-02-08	GMBS3	SG	2009	2200	2200	2200	2200	2200	190	9.00%	10
2017-02-16	GMBSLG	SG	2009	2180	2180	2,180.00	2180	2180	200	10.00%	5
2017-02-23	GMBSLG	SG	2009	2310	2310	2310	2310	2310	130	5.00%	5
2017-02-24	GMBSLG	SG	2009	2310	2310	2310	2310	2310	0	0.00%	5
2017-03-10	GMBS3	SG	2009	2400	2400	2400	2400	2400	200	9.00%	11.4
2017-10-17	GMBS3	KM	2009	1860	1860	1860	1860	1860	0	0	30
2017-11-23	GMBS3	SG	2009	1800	1800	1800	1800	1800	600	25.00%	5.4
2017-11-23	GMBS3	SG	2010	1800	1800	1800	1800	1800	0	0	6.2
2017-11-27	GMBS3	KM	2010	1800	1800	1800	1800	1800	0	0	25.8
2017-11-28	GMBSLG	SG	2009	1700	1700	1,700.00	1700	1700	610	26.00%	5
2017-11-28	GMBS3	KM	2010	1800	1800	1800	1800	1800	0	0.00%	5.9
2017-11-29	GMBSLG	KM	2010	1700	1700	1700	1700	1700	0	0	10.5
2017-11-29	GMBSLG	SG	2009	1720	1721	1730	1720	1723	21	1.00%	40
2017-12-01	GMBS3	SG	2009	1800	1800	1800	1800	1800	0	0.00%	41.7
2017-12-05	GMBS3	KM	2010	1800	1800	1800	1800	1800	0	0.00%	33.4
2017-12-11	GMBS3	KM	2010	1780	1780	1780	1780	1780	20	1.00%	15.5
2017-12-19	GMBS3	SG	2010	1700	1700	1700	1700	1700	100	5.00%	5
2017-12-20	GMBS3	SG	2010	1700	1700	1700	1700	1700	0	0.00%	21.5