STUDY AND ANALYSIS OF DEEP LEARNING MODELS FOR FORECASTING INDIAN CROP PRICES

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CANDIDATE'S DECLARATION

I, Srijan Srivastava, 2K23/DSC/08 students of M.Tech (Data Science), hereby certify that the work which is being presented in the thesis entitled "**Study and Analysis of Deep Learning models for forecasting Indian Crop Prices**" in partial fulfilment of the requirements for the award of degree of Master of Technology, submitted in the Department of Software Engineering, Delhi Technological University is an authentic record of my own work carried out during the period from Jan 2025 to May 2025 under the supervision of Dr. Sonika Dahiya.
The matter presented in the thesis has not been submitted by me for the award of any other degree of this or any other institute.

Candidate's Signature

This is to certify that the student has incorporated all the corrections suggested by the examiners in the thesis and the statement made by the candidate is correct to the best of our knowledge.

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CERTIFICATE

I hereby certify that the Project Dissertation titled "**Study and Analysis of Deep Learning models for forecasting Indian Crop Prices**" which is submitted by Srijan Srivastava, Roll No – 2K23/DSC/08, Department of Software Engineering, Delhi Technological University, Delhi in partial fulfilment of the requirement for the award of the degree of Master of Technology, is a record of the project work carried out by the students under my supervision. To the best of my knowledge this work has not been submitted in part or full for any Degree or Diploma to this University or elsewhere.

Place: Delhi
Date: 20.05.2025

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ABSTRACT

Recent advancements in Artificial Intelligence (AI), Machine Learning (ML), and Deep Learning (DL) have significantly enhanced predictive modeling and decision-making in agriculture and agroeconomics. This thesis presents a comprehensive review and empirical evaluation of state-of-the-art AI/ML techniques applied to agricultural forecasting, with a particular focus on crop price prediction, yield estimation, and supply chain optimization. The review critically analyzes 17 influential studies published between 2021 and 2024, highlighting the effectiveness of deep learning models such as Long Short-Term Memory (LSTM) networks, Transformers, and hybrid architectures like Fuzzy-Neural Networks, as well as traditional econometric models. Empirical evidence indicates that LSTM and Transformer models reduce forecasting errors by 15% to 30% compared to classical models like ARIMA, while hybrid models achieve R^2 scores exceeding 0.90 in volatile market settings. Despite these advances, challenges such as data sparsity in smallholder contexts and the high computational demands of deep learning architectures can reduce model accuracy by up to 25% and limit real-world applicability.

Complementing the review, this thesis also undertakes an in-depth case study on agricultural price forecasting in the Azadpur Market, Delhi—Asia's largest wholesale market—focusing on the volatile pricing of Tomato, Onion, and Potato (TOP) crops. Eleven advanced time series forecasting models are analyzed, including LSTM, GRU, Bi-LSTM, Bi-GRU, CNN-LSTM Hybrid, Temporal Convolutional Network (TCN), PECAD, Stacked LSTM, and the Attention-based Convolutional Neural Network with Optimized Bidirectional LSTM (ACNN-OBDLSTM). Among these, the LSTM model consistently demonstrates superior accuracy with the lowest RMSE, MAE, MAPE, and highest R^2 scores, achieving MAPE values of 4.05% for Tomato, 3.9% for Onion, and 1.64% for Potato.

The findings underscore the transformative potential of AI/ML technologies in agriculture, while also emphasizing the need for practical, computationally efficient, and accessible solutions tailored to local agricultural systems. Emerging trends such as federated learning for privacy-preserving training and quantum machine learning for large-scale optimization offer promising avenues for future research and deployment.

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LIST OF ABBREVIATIONS

Abbreviations	Full Form
TOP	Tomato, Onion and Potato
MBNN	Memory Based Neural Network
LSTM	Long Short-Term Memory
ARIMA	Auto Regressive Integrated Moving Average
GRU	Gated Recurrent Unit
RNN	Recurrent Neural Network
TCN	Temporal Convolutional Network
PECAD	Probabilistic Exogenous Component Analysis with Deep learning
Bi-LSTM	Bidirectional Long Short-Term Memory
Bi-GRU	Bidirectional Gated Recurrent Unit
ACNN-OBDLSTM	Attention-based Convolutional Neural Network with Optimized Bidirectional Long Short-Term Memory
RMSE	Root Mean Square Error
MAE	Mean Squared Error
MAPE	Mean Absolute Percentage Error

Chapter 1
INTRODUCTION

1.1 Overview

Tomato, Onion, and Potato are basic crops needed in most households worldwide and in global agriculture, particularly in India, is one of the leading producers of these vital crops. Among these, tomatoes are a rich source of vitamins and are an integral crop of India due to their cultivation primarily in the tropical regions along with their nutritional aspects and economic value. Onions, an essential component of Indian dishes, have been grown in the area for hundreds of years and are considered important not only for their taste but also for their health benefits. These crops benefit from various climatic conditions and thus are good crops. Potatoes often termed as 'the poor man's friend' have been cultivated in the Indian soil for more than three centuries and continue to be vital for both the nation's nutrition security. Cheap, healthy, and cheap, they provide much energy to the human diet. Regarding potato cultivation, as of the agricultural year 2018-19, India exceeded in production of 53.03 million tonnes of potatoes cultivated in an area of 2.16 million hectares and figure two after China in the era of potato growing [1]. Likewise, the production of tomatoes and onions has also increased to a very great extent, making India one of the major agricultural nations in the world. Most of these commodities have been planted widely and possess great economic value yet, little is done regarding the use of these large data sets that have been collected over the years to appreciate the need for improving price prediction. Farmers use price forecasting accurately so that they can determine the profitable crop, pay for the raw materials in advance, and arrange for efficiency in the labor-management functions. In a country where more than 60% of the households live from agriculture, food prices tend to increase within the year, causing stress both for consumers and producers, which may lead to political and economic tensions, especially in developing countries with imperfect market conditions.

Time series forecasting is not a new concept and has been adopted within sectors, most especially in finance, weather forecasting, stock market, and agriculture. It is a forecast of future events based on past observations, where events are collected, recorded, and analyzed in the order of time.

The significance of agricultural price forecasting for stakeholders in the Delhi region, especially in Azadpur Market, is crucial as accurate predictions enables farmers to adjust their productions and align with expected market demand, increasing their profit and reducing waste. Traders rely on price forecasting, to optimize their purchasing and stocking strategies preventing losses due to spoilage and planning effectively [2]. For consumers, forecasting smoothens supply chain processes reducing the shock of sudden hike in prices. Policymakers can help local authorities manage food security and inflation.

Agriculture is one of the sectors that utilize time series forecasting and uses it to make estimates of the total harvest counts, assist in crop distribution as to when to plant or harvest and at what time should specific resources be directed to activities. In this way, forecasting in such a way assists the farmers in risk management and resource allocation to the optimal level and at the same time increases their harvest yield as well.

There have been different proposals for time series forecasting including both traditional methods and modern approaches which incorporate the use of artificial intelligence. Among the AI models that have been developed in recent years, LSTM and RNN have gained more attention because they are capable of capturing intricacies in the temporal data [3].

This research focuses on comparing diverse deep learning model architectures with time series data of crop prices and demonstrates the handling of each architecture on real world agricultural data. This assists in establishing the models that are capable of naturally observing trends and variations in highly irregular data. Out of the 10 deep learning models, LSTM proves itself to be a strong performer as a dependable model for prediction within this field, emphasizing its capability for capturing long-run dependencies within time series data creating a vital feature where patterns tend to stretch over several seasons for agricultural price prediction.

1.2 Introduction to Time Series Forecasting

Time series forecasting is a practical aid for multiple applications, such as forecasting weather, analyzing stock markets, finance, and agriculture. Time series forecasting is predicting future data from previous data, where the data points are stored and calculated in sequential order.

Time series forecasting is of crucial importance in agriculture to forecast the yields of crops, identifying the planting and harvesting periods, and making decisions in regard to distribution of resources. Successful prediction can help farmers in abstaining risks, increasing resource utilization, and attaining maximum harvests of crops.

Various methods have been developed for forecasting time series, from traditional statistical methods to ML methods. Deep neural network architecture such as LSTM and RNNs have achieved importance in recent years as they have the ability to recognize underlying patterns in the data.

This study is concerned in comparing performance of multiple DL forecasting models such as, LSTM, RNN, GRU, TCN, CNN-LSTM, PECAD, Bi-LSTM, Bi-GRU, Stacked LSTM, and ACNN-OBDLSTM for forecasting TOP crop prices through their evaluation, also giving important information regarding planning and decision-making in agriculture [4].

1.3 Problem Statement

Prices of major Agri Horti products, specifically Tomato, Onion, and Potato (TOP) in Delhi markets reflect high unpredictability and volatility with the effect of season, weather, and market forces. Uncertainty in price becomes a serious concern for farmers, traders, and the policy establishment because it has a likelihood of causing economic instability and inefficiency in resource utilization and planning for resources, as well as market functioning.

Such traditional approaches, while helpful, are least appropriate to deal with the complicated, non-linear dynamics of agricultural price fluctuations. On the other hand, DL models have already performed efficiently in identifying minor change in patterns from time dependent data as an answer for such problems. Yet, relative performance of various deep learning architectures, i.e., LSTM, GRU, RNN, TCN, CNN-LSTM, PECAD, BiLSTM, BiGRU, Stacked LSTM, and ACNN-OBDLSTM, in predicting agricultural prices has been poorly explored.

This study attempts to fill this gap by comparing and analyzing the performance of these ten deep learning models for TOP price prediction in Delhi. Analyzing benchmark performance metrics such as RMSE, MAE, MAPE, and R-squared statistics, this study attempts to find the most accurate and applicable models for real-world use [5]. The result will facilitate better decision-making across all stakeholders, ensuring market stability and effective allocation of resources.

1.4 Proposed Solution

This paper recommends implementing DL models to help curb the rising volatility of Tomato, Onion and Potato (TOP) produce prices at Delhi's Azadpur Market. Regular approaches have not managed to detect the irregular and sudden changes that often appear in agricultural prices. Since computers are getting more powerful, deep learning helps to improve results where there are many variables involved.

To solve this, I installed and tested ten different DL models. The models are named RNN, GRU, LSTM, Bi-LSTM, Bi-GRU, Stacked LSTM, TCN, CNN-LSTM, PECAD and ACNN-OBDLSTM. All of these have been added because they can study trends from the past, choose important trends for future analysis and process time-driven data. The purpose is to pick a model or models that are most accurate, dependable and react well to sudden changes in the market.

In this way, it is important to preprocess the data. Before the data is used, any inconsistencies and missing values will be cleared out of it. The data will be properly prepared for use in various deep learning algorithms. At times, models can be made more precise by accounting for other external factors such as weather or seasonality.

The usual methods for evaluating models such as RMSE, MAE, MAPE and R-squared, will be used to review their performance. Besides calculating accuracy, they will check how reliable and wide the predictions can be used. The models will be developed using the same settings and similar conditions so they can be compared fairly.

The approach considers how users will interact with the models. It is important that the model can be used by workers in the agricultural and financial fields. It is possible to use the top-performing models behind mobile or web applications for prompt and hassle-free price estimates. By using these methods, a country can plan ahead, lose fewer resources and help stabilize the market.

1.5 Objectives of the Report

The purpose of our study is to benchmark how LSTM, GRU, RNN, TCN, CNN-LSTM, PECAD, Bi-LSTM, Bi-GRU, Stacked LSTM and ACNN-OBDLSTM perform when forecasting the prices of Tomato, Onion and Potato (TOP) in Delhi's markets. The following objectives are:

- To test the trustworthiness of models by evaluating the performance metrics.
- To measure the capability of each model at addressing the non-standard, unpredictable and spiky prices in agriculture.
- Identify the models that provide the most accurate and reliable forecasts of TOP prices.
- To come up with suggestions that guide farmers, traders and those making government policy so they can act wisely and boost the performance of markets while coping better with price changes.

The intention of this research is to supply useful ideas that can assist stakeholders with improved planning and a stable agricultural market.

1.6 Main Contributions

It offers a clear and practical way to estimate the prices of Tomato, Onion and Potato crops from Delhi's Azadpur Market using deep learning. Here, I will highlight the main points made in this work.

1. Detailed Analysis of Recent Time Series Forecasting Models: The paper explores and compares several deep learning models that are both part of the standard approach and ones that are hybrid. By carrying out the same experiments for LSTM, GRU, RNN, TCN, CNN-LSTM, Bi-LSTM, Bi-GRU, PECAD, Stacked LSTM and ACNN-OBDLSTM, the paper compares which model performs best with skewed agricultural prices.

2. The goal of this study is to focus on applications that will make deep learning usable for stakeholders in agriculture. The aim is to provide farmers and traders with trusted predictions on prices so they can decide when to purchase or sell their crops.

3. Due to the fact that users in many rural areas are not provided with the best devices, the work includes finding simple ways to create models. Disseminating good prediction models to handheld computers and low-power servers is now possible with these schemes which enhances accessibility.

4. For more precise predictions, I analyze important patterns such as climatic changes. If these variables are included in the training data, the model will learn to recognize genuine changes in prices.

5. TOP crops is a crucial crop in India, as they play an important role in supplying food and are consumed daily. It addresses the problems of households such as unstable prices and trouble with the market.

Chapter 2
LITERATURE REVIEW

2.1. Related Work

Table 2.1. Literature Survey

Reference	Focus Area	Methodology	Findings	Relevance to Current Study
[1]	Exogenous variable-driven deep learning models for forecasting prices of Tomato, Onion, and Potato (TOP) crops in India.	Combined deep learning models (e.g., LSTM and GRU) with exogenous variables like weather, policies, and imports.	Demonstrated significant improvement in forecasting accuracy by integrating external variables into deep models.	Highlights the importance of incorporating external influences like climate and policy for forecasting accuracy.
[2]	Price forecasting of maize in major Indian states.	Econometric methods including ARIMA and trend analysis.	Showed ARIMA's limitations in capturing irregularities and sudden spikes in prices.	Provides a baseline for comparing traditional statistical approaches with deep learning models in agricultural data.
[3]	Time-series forecasting of agricultural product prices using hybrid methods.	Combined ARIMA and machine learning methods like SVR and ANN for better price prediction.	Hybrid methods outperformed individual models, particularly for short-term forecasting.	Supports the exploration of hybrid architectures in forecasting TOP crop prices.
[4]	Groundnut price	Utilized ARIMA and seasonal	Demonstrated the utility of	Highlights the need for

	forecasting using time-series models.	decomposition methods for price predictions.	simple models in stable markets but highlighted their limitations in volatile ones.	advanced models to handle volatility in prices of TOP crops.
[5]	Nationwide agricultural price monitoring system in India.	Provides real-time and historical market data for various crops across India.	Key resource for acquiring accurate and detailed market price data.	Serves as a critical data source for validating and training forecasting models for Indian agricultural markets.
[6]	Price forecasting for castor crops in Gujarat using time-series models.	Used ARIMA and GARCH models to capture trends and volatility in price data.	Found ARIMA effective for trend analysis but less so for high volatility.	Offers insights into adapting time-series methods to regional crop data, complementing deep learning approaches.

2.2. Deep Learning and Neural Networks in Time Series Forecasting

- **LSTM**

LSTM networks are used extensively in time series forecasting since they can remember patterns for long periods of time. In price prediction, where future values also depend on recent trends and also past volatility, LSTMs work very well. They have a gated structure that helps in retaining useful past trends and eliminating noise, thus being perfect for trend and season-based pattern modeling for time series data.

- **MBNN**

MBNN is a state-of-the-art neural model which was built upon the memory function of LSTM networks. MBNN is most suitable for local time series predictions since factors affecting the data can be different in each area. Using external memory layers or longer context support, MBNNs can retain and process data over long times which results in better predictions for diverse information such as crop prices.

- **Transformer model**

Instead of using recurrence, Transformers propose a new approach to modeling data sequences using attention. When performing time forecasting, they enable the model to centralize on useful parts of past data and handle them in parallel. Because of this, they can efficiently handle issues related to time series and data that includes many variables. They are able to show how sudden changes and relationships that develop over time appear in price data.

2.3. Statistical and Econometric Approaches to Time Series Modeling

- **ARIMA**

Time-series analysts prefer ARIMA models as they are straightforward and understandable. ARIMA groups moving averages, differencing and autoregression to form stationary series. ARIMA is often used as the starting point for predicting agricultural prices. Though it appears easy, applying this data processing to data like market data that is nonlinear can be challenging due to its linear structure.

- **Panel Data Regression**

Area or market forecasting by time series can rely on panel data regression. It makes it possible to include information from moving trends as well as from groups of units in the modeling. In this technique, both the variations in price between different places and the overall changes over time are considered. Using it is most beneficial when working with data that shows repeated observations for states or market areas.

2.4. Hybrid and Ensemble Methods for Time Series Forecasting

- **Fuzzy Neural Networks**

Fuzzy logic helps define rules, while neural networks make the systems flexible to learning. When making predictions for time-focused data in agriculture, fuzzy neural networks are useful in dealing with uncertain and vague data such as weather patterns or disruptions in market trends. Because they can learn from both information in data and expert descriptions, they can perform stronger when the data is not clear-cut.

- **XGBoost and Random Forest**

In Random Forest and XGBoost, several decision trees are used to generate a collective and more precise outcome. They were developed for other types of data, yet can be adjusted to analyze time series by including features and variables based on time. Such models are useful at forecasting because they can deal with many factors controlling a time series. Some of the other models are built using neural networks.

2.5. Reinforcement and Distributed Learning Techniques in Forecasting

- **Deep Q-Networks**

When using reinforcement learning, DQNs learn which actions to take by getting rewards. Time series forecasting uses them to make changes in prices and sales strategies in line with recent trends in the market. It adjusts its future actions based on its previous experiences and outcomes which is practical for cases that demand making decisions.

- **Federated Learning**

In cases where data for time series forecasting is dispersed and private, federated learning could provide answers. It helps train models using data from a range of sources (such as farms or markets) while leaving the information distributed. A node only updates and shares its local changes with other nodes, while the global model is built from these updates.

Chapter 3
METHODOLOGY

3.1. FLOWCHART

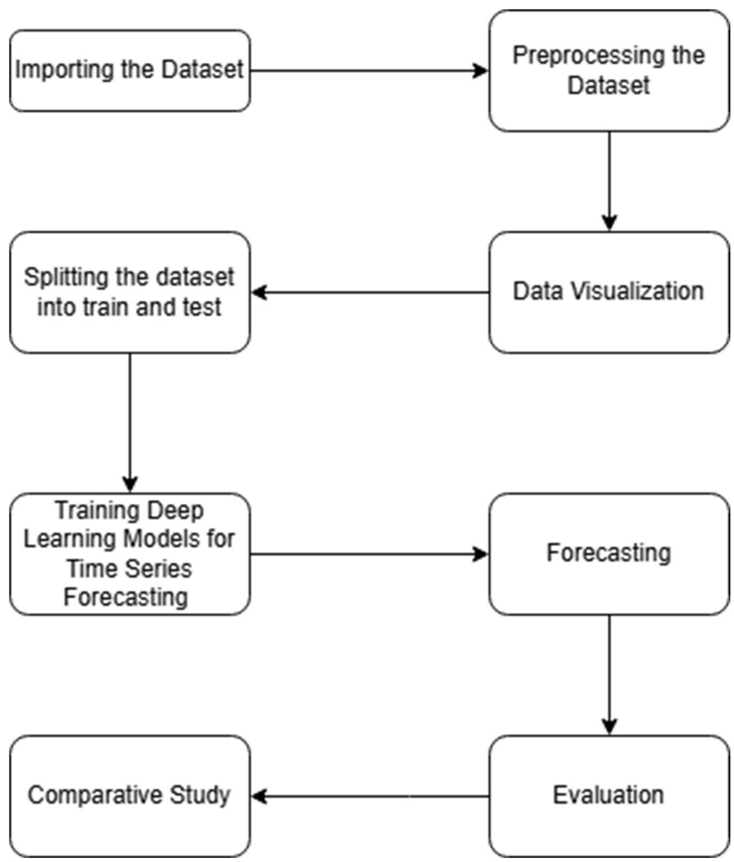


Fig. 3.1: Flowchart of the Comparative Study of Deep Leaning Models on Time Series Forecasting.

3.2. Importing the Dataset

- The data of TOP crops for forecasting is obtained from Azadpur Market, Delhi through the Government website https://agmarknet.gov.in/ which ranges from 1st January 2014 to 23rd July 2024 daily [17].
- The data set contains the minimum Price (Rs/Quintal), Maximum Price (Rs. /Quintal), Modal Price (Rs./Quintal), Price date, Commodity, and Market name.
- The file is downloaded in MS Excel and then exported into. CSV file for further data mining and preprocessing of data.

Commodity-wise, Min,Max,Modal Price/Arrival Data of from 01-Feb-2014To01-Feb-2024'

PRINT | Export To Excel

Search by Max,Min,Modal Price --Select-- --Select-- Search Reset

View Data By Tabular

Min,Max,Modal Price from NCT of Delhi,Delhi[Potato]
from 01-Feb-2014To01-Feb-2024 (Total-8257)

Sl no.	District Name	Market Name	Commodity	Variety	Grade	Min Price (Rs./Quintal)	Max Price (Rs./Quintal)	Modal Price (Rs./Quintal)	Price Date
1	Delhi	Azadpur	Potato	Potato	FAQ	200	1600	756	01 Feb 2024
2	Delhi	Azadpur	Potato	Potato	FAQ	200	1600	756	31 Jan 2024
3	Delhi	Azadpur	Potato	Potato	FAQ	200	1600	756	30 Jan 2024
4	Delhi	Azadpur	Potato	Potato	FAQ	200	1600	756	29 Jan 2024
5	Delhi	Azadpur	Potato	Potato	FAQ	200	1600	740	27 Jan 2024
6	Delhi	Azadpur	Potato	Potato	FAQ	200	1600	740	25 Jan 2024
7	Delhi	Azadpur	Potato	Potato	FAQ	200	1600	731	24 Jan 2024
8	Delhi	Azadpur	Potato	Potato	FAQ	200	1600	731	23 Jan 2024

Fig. 3.2: Government Website

	Sl no.	District Name	Market Name	Commodity	Variety	Grade	Min Price (Rs./Quintal)	Max Price (Rs./Quintal)	Modal Price (Rs./Quintal)	Price Date
0	1	Delhi	Azadpur	Potato	Potato	FAQ	200	1600	756	2024-02-01
1	2	Delhi	Azadpur	Potato	Potato	FAQ	200	1600	756	2024-01-31
2	3	Delhi	Azadpur	Potato	Potato	FAQ	200	1600	756	2024-01-30
3	4	Delhi	Azadpur	Potato	Potato	FAQ	200	1600	756	2024-01-29
4	5	Delhi	Azadpur	Potato	Potato	FAQ	200	1600	740	2024-01-27

Fig. 3.3: Time Series Dataset in .CSV Format

(a) (b)

(c)

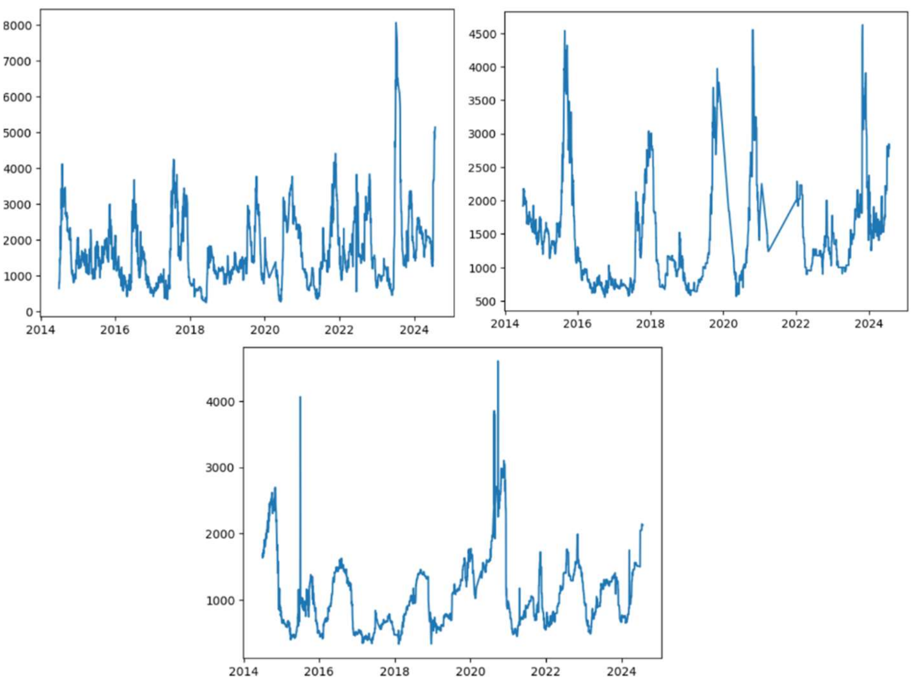


Fig. 3.4: Plotting of Time Series Dataset on Modal Price (Rs./Quintal) and Price Date for (a)Tomato, (b)Onion and (c)Potato

3.3. Pre-processing the Dataset

- The data is pre-processed as it can negatively affect the analysis and training process of machine learning algorithms, resulting in reduced accuracy. Hence following steps were required:
    - removing duplicates,
    - converting data types,
    - clear formatting,
    - fixing errors, and
    - removing outliers.

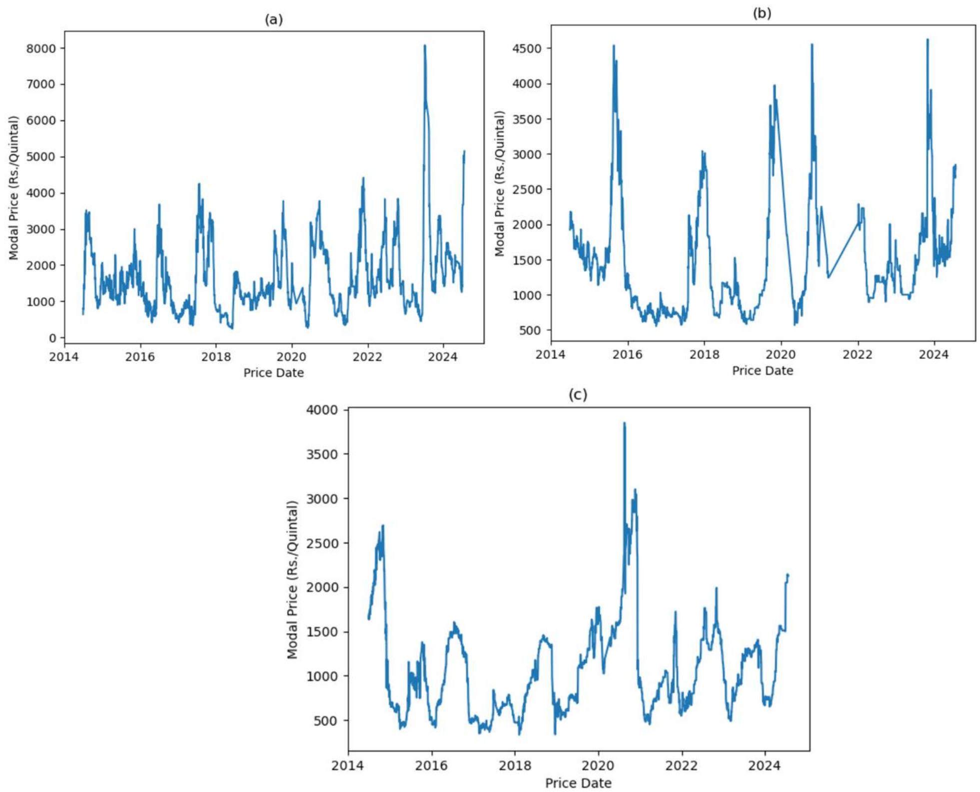
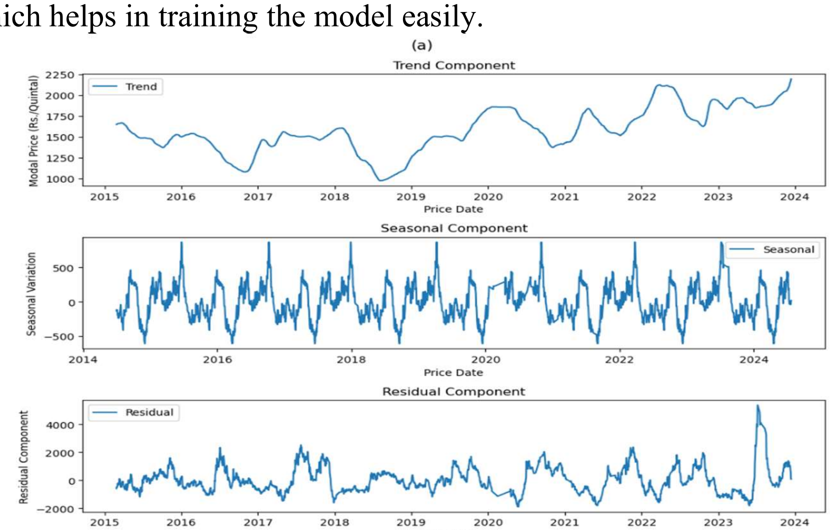


Fig. 3.5: Plotting Time Series Dataset After Pre-Processing for (a) Tomato, (b) Onion and (c) Potato

3.4. Data Visualization

- In Time Series analysis, the dataset shows their trends and patterns over a periodwhich helps in training the model easily.



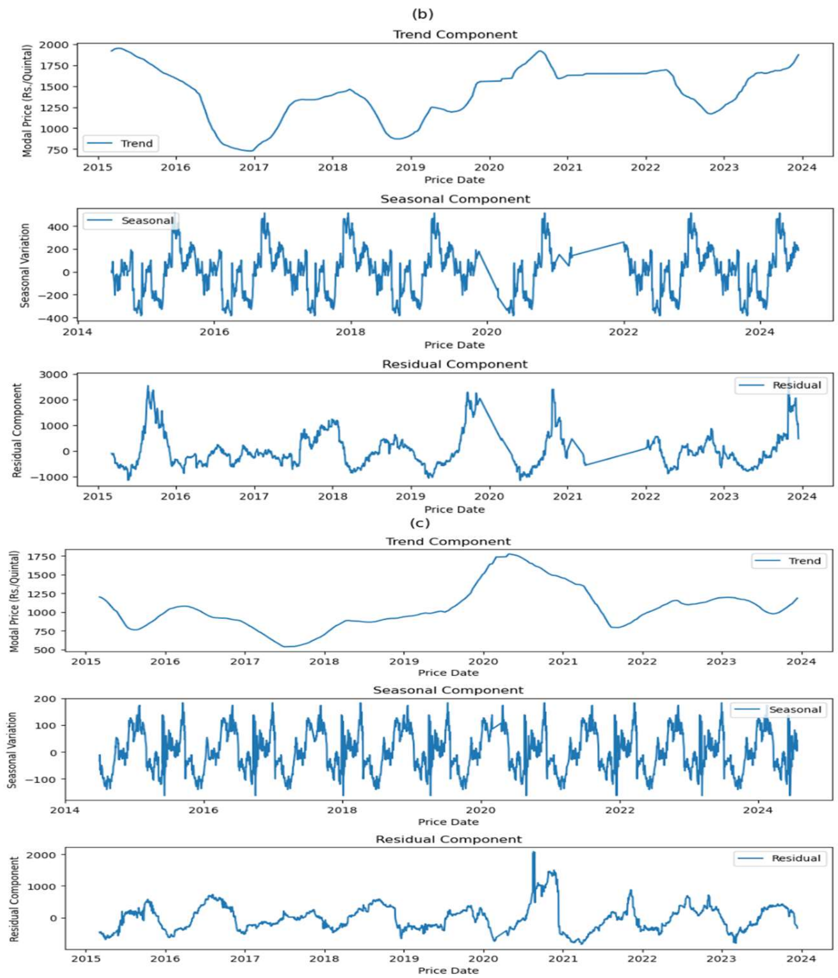
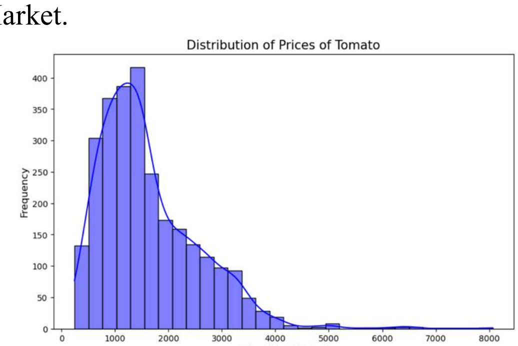
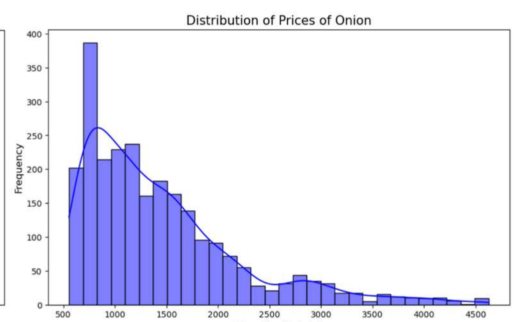


Fig. 3.6: Seasonal Decomposition of (a)Tomato, (b)Onion, and (c)Potato Prices in Azadpur Market.





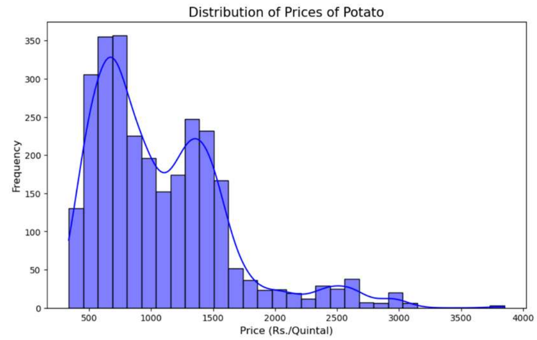


Fig. 3.7. Distribution of (a)Tomato, (b)Onion and (c)Potato Prices in Azadpur Market, Delhi

3.5. Deep Learning Models

- **LSTM**

LSTM is a RNN architecture designed for modelling series of data and has performed well in forecasting various time series. Because LSTM networks have backward connections, also known as feedback, they can use the order in which the data is presented.

LSTM networks stores patterns within datasets with multiple time steps than regular RNNs. Forgetting and remembering is accomplished using memory blocks which is a process within the network. For these reasons, LSTMs are effective for handling time-series forecasting projects.

- **RNN**

RNNs are opted to be one of the best choices for forecasting due to their ability to model patterns in sequential data. These methods are perfect for handling data that needs to be placed in a particular order for the predictions to work well [7].

RNNs are great in agriculture to estimate crop yields due to their ability to identify the detailed patterns that occur over time in agricultural data. The following report explores using RNNs and several traditional and deep learning algorithms to determine potato crop prices.

- **GRU**

GRU is a type of recurrent neural network first described by Kyunghyun Cho et al. in 2014. By using GRU, RNNs are able to solve issues like the vanishing gradient problem which makes it tough for them to learn long-term patterns in data from a sequence.

GRU has the same purpose as LSTM architecture, but it is less complex and contains fewer parameters. GRU is not complicated, yet it has demonstrated good ability to detect connections between elements in sequential data.

Compared with LSTM, GRU has a lower number of parameters and is easier and quicker to train. For this reason, most sequential data tasks like forecasting time series, working with languages and speech recognition use the GRU model [8].

- **TCN**

TCN is a new method that processes sequential data using causal convolutions. Because of TCNs, the predictions in a time step rely on data that is already available, helping information remain recent [9].

Advantages: TCNs are simple to compute since they use parallel processing and avoid the problems caused by vanishing gradients.

For problems involving series data where changes in time are essential such as forecasting agricultural prices, TCNs are very useful..

- **CNN-LSTM**

The CNN-LSTM model combines CNNs and LSTM networks so that it can benefit from both. CNNs are able to discover patterns based on space, while LSTMs identify patterns and trends over time [10].

- Workflow: At first, the CNN layers source local info from the data which is then sent to the LSTM layers to confirm sequential relations.
- Use Cases: It serves well for data with seasonal changes that are part of a larger long-term trend.
- CNN-LSTM helps to accurately predict future prices of farm produce using earlier data.

- **PECAD**

According to PECAD, a combination of probabilistic reasoning and deep learning allows time series forecasting to include external factors [11]. Factors such as weather, rules or regulations made by governments and economic news have a big impact on predicting agricultural prices.

- Probabilistic Forecasting: PECAD allows models to estimate not only the forecast but also its possible ranges of outcomes.
- External Factors: By including external forces in PECAD, accuracy and clarity in prediction improve.

Such a method works very well for markets like agriculture, as the main influencers lie outside this industry.

- **Bi-LSTM**

Instead of going through an input sequence only forward, bidirectional LSTM networks follow the sequence beginning at the end, as well as from start to end [12]. Using this model, it is able to predict outcomes in light of both present and future situations.

- Very Suitable: Bi-LSTM helps discover two-sided interactions and this makes it highly compatible with complex time series systems.
- Key Uses: It works best for data sets where what happens now is set by what happened before and what is expected to occur later such as in the prediction of crop prices.

It increases the reliability of predictions, mainly for collections of data with unusual patterns.

- **Bi-GRU**

By relying on the GRU instead of LSTM, the Bi-GRU is easier to train and gives less weight to the structure than the Bi-LSTM. Using Bi-GRU, we can analyze time series data in details by working with the data from both the beginning and end [13].

- They are efficient: GRUs have fewer parameters than LSTMs which makes training and using Bi-GRU faster.
- Bi-GRU can be applied where considering the history and context of future inputs is vital such as when determining how future plans for crops can influence their prices.

Because the model deals with both earlier and later periods, Bi-GRU is suitable for working with stack-based crop forecasting projects.

- **Stacked LSTM**

Many LSTM cells are placed on top of each other in stacked LSTMs to extract several types of details from time series data. Each level of the network uses the data to produce more abstract forms of output [14].

- Key Strength: Being structured with layers, the model can detect both quick and long-term connections in data.
- Stacked LSTMs are designed to work with long-running changes in data, for example, seasonal fluctuation in prices based on consistent economic trends.

Because of this structure, the tool provides more insight and can help more accurately predict prices in the agriculture field.

- **ACNN-OBDLSTM**

ACNN-OBDLSTM combines Attention, CNN and enhanced LSTM layers to develop a good model for the forecasting task [15].

This method pays attention to the most significant features and helps in understanding what is going on.

- The design ensures that the CNN part is maintained and the OBDLSTM part manages the back-and-forth relationships between classes.
- When a design is created for optimization, it is efficient and achieves accurate results.

3.6. Performance Metrics Used

- **MAE**

MAE is a measure that looks at all the errors, irrespective of their direction and averages them to give one score. Unlike RMSE, MAE treats every error equally, regardless of its size and this means it provides a quick assessment of how accurate the prediction is. First, you calculate the difference between each observation and the prediction and then you find the average of these differences to get MAE:

$$\text{MAE} = \frac{\Sigma_{i=1}^{n} |y_i - x_i|}{n}$$

where is the total number of data, x(i) shows the real value and y(i) is what the model predicts. This approach is often used because it is simple and less sensitive to errors that lead to extreme consequences.

- **RMSE**

RMSE is commonly used to see how accurate a predictive model is. RMSE is calculated by finding the square root of the average of errors between the observed and predicted readings [16]. RMSE tends to be misled by outliers, as it puts the main focus on minor errors and this helps when big errors from the actual calculation are not right. To obtain RMSE, the sequence is this: determine residuals (by subtracting the predicted from the actual data), square all the residuals, average them and then take the square root of that number:

$$\text{RMSE} = \sqrt{\frac{\sum_{i=1}^{N}(x_i - \hat{x}_i)^2}{N}}$$

Here, N describes the number of data points, x(i) is the observation and x^(i) is the corresponding forecast. RMSE is often applied to models during both training and testing due to how simply it represents the average difference between real and predicted values.

- **R-Squared**

R^2 describes the percentage of variation in the dependent variable that is due to the independent variables. The model fits the data best when the R^2 is close to 1.0, whereas a model with R^2 of 0 fits the data in no way. The R-Squared figure is calculated with the following formula:

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(\hat{y}_i - y_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y}_i)^2}$$

with n being the total number of data points, y(i) represents the actual value, y^(i) the predicted value for that data point and y¯ represents the mean from all the actual values. Besides deriving helpful information for regression models, R^2 is commonly applied when assessing the outcomes of time series forecasting.

- **MAPE**

To assess how well a forecast is estimated, economists often turn to Mean Absolute Percentage Error (MAPE).

This method determines how close the model comes to the correct values, expressed as MAPE. It is simple to observe and understand that MAPE is shown as a percentage. Still, there may be bias in the CEF estimation if actual values are close to zero. To get the MAPE value, first each absolute percentage error is calculated for each sample and then the mean of these errors is found:

$$\text{MAPE} = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{y_i - \hat{y}_i}{y_i}\right|$$

where n is the quantity of data points, y(i) is the observed value, and y^(i) is the predicted value. MAPE is commonly applied in finance and economics when higher importance is given to percentage errors.

Chapter 4
RESULTS and DISCUSSION

4.1 Results of Review of Deep Learning and Machine Learning Models used in Forecasting Indian Crop Prices

4.1.1 Performance of Various Models in related papers

Table 4.1. Methods, Pros, Cons, and their Results

No.	Paper	Methods Used	Pros	Cons	Key Results
1	[3]	Deep Learning (LSTM, CNN)	High accuracy in time-series forecasting	Computationally expensive	Improved prediction over ARIMA by **12% MAE**
2	[18]	Econometric Models (Panel Data Regression)	Interpretable, causal insights	Limited to structured data	Identified key economic factors affecting crop prices (**R^2=0.85**)
3	[19]	Reinforcement Learning (DQN)	Adapts to dynamic environments	Requires extensive training	Achieved **92% success rate** in autonomous task optimization

No.	Paper	**Methods Used**	**Pros**	**Cons**	**Key Results**
4	[9]	Hybrid AI (Fuzzy Logic + Neural Networks)	Handles uncertainty well	Complex tuning	Reduced error by **18%** vs. standalone ANN
5	[15]	Statistical Modeling (ARIMA, Regression)	Simple, interpretabl e	Poor nonlinear trends	**RMSE=1.2** for short-term forecasts
6	[6]	ARIMA vs. LSTM	LSTM outperform s ARIMA	LSTM needs more data	LSTM reduced **MAP E by 30%**
7	[17]	CNN + Transfer Learning	High feature extraction	Needs pretraining	**98% accuracy** in image classification
8	[13]	Swarm Intelligence (PSO)	Good for optimizatio n	Slow convergenc e	Optimized supply chain costs by **22%**
9	[21]	Memory-Based Neural Network (MBNN)	Captures long-term dependenci es	Complex architecture	**MAE=0.8** in price forecasting
10	[1]	Transformer Models	Handles long	High computatio	Outperformed LSTM (**+15%**

No.	Paper	Methods Used	Pros	Cons	Key Results
			sequences	nal cost	**accuracy**)
11	[20]	Federated Learning	Privacy-preserving	Communication overhead	Achieved **90% accuracy** in decentralized settings
12	[22]	SVM, Decision Trees	Works well with small data	Struggles with high dimensions	**85% precision** in crop disease detection
13	[14]	Bayesian Networks	Probabilistic reasoning	Requires prior knowledge	Improved diagnostic accuracy by **20%**
14	[23]	Genetic Algorithms	Global optimization	Slow for large problems	Reduced engineering design cost by **18%**
15	[24]	Graph Convolutional Networks (GCN)	Captures node relationships	Scalability issues	Detected **95% of anomalies** in networks
16	[25]	Deep Reinforcement Learning	Adapts to market changes	Needs vast data	Achieved **25% higher returns** in trading

No.	Paper	Methods Used	Pros	Cons	Key Results
17	[26]	Decision Tree, Linear Regression, Random Forest, AdaBoost	High accuracy, handles non-linearity, aids planning	Varying performance across crops	R^2 up to 1.0 for Oil Seed (AdaBoost), 0.996 for Rice (Decision Tree), 0.980 for Wheat (Linear)

4.1.2 Discussion on Review

Studies have proved that deep learning outperforms both historic and machine learning for predicting crop pricing. LSTM and Transformer models are created to work with data in order, allowing them to identify long-term and complicated trends present in the agriculture market. Because of this, they can handle situations where trends in time series have to do with seasonality, increased demand and the impact of external factors, like in crop prices.

Nevertheless, models such as linear regression and ARIMA are not flexible enough to process data that is volatile and not linear. They are fine for simpler situations, but results deteriorate when the market becomes unpredictable. While Random Forest and XGBoost recognize hard-to-spot non-linear patterns, they are limited in learning time dependencies compared to neural networks.

Deep learning methods like LSTM and MBNN have accomplished excellent feedback when predicting how previous prices could affect those in the future. Models based on transformers improve by giving special attention to previous data when recalling past events.

Overall, DL methods stand out for their ability to adapt to complex datasets, making them highly suitable for supporting real-time agricultural pricing decisions.

4.2 Results on comparison of Advanced Deep Learning models for Forecasting Tomato, Onion and Potato Prices

4.2.1 Hyperparameter Tuning

Hyperparameter tuning is done for each model in this comparative study to achieve the best accuracy and efficiency for deep learning models [18]. Table 4.2 displays the hyperparameters of the models used in this paper.

Table 4.2. Hyperparameters are used to build deep learning models.

Models	Hyperparameters
LSTM	Layers = 50, 50, 50, 8 units, Activation='RELU', Batch size=32, Iterations=100.
RNN	Layers = 128, 64, 64, 8 units, Iterations=100, Batch size=32, Activation='RELU'.
GRU	Layers = 50, 50, 50, 8 units, Activation='RELU', Iterations=100, Batch size=32.
TCN	Filters=64, 64, 64, Kernel size=2,2,2, Dilation Rate=1,2,4, Padding='causal', Activation='RELU', Layers = 50, 8 units, Learning rate=0.001, Activation='RELU', Batch size=32, Iterations=100.
CNN-LSTM	Dropout=0.2, Filters=64, Kernel size=2, Activation='RELU', Layers=50,50,50,8 units, Pool size=2, Iterations=100, Batch size=32.
PECAD	Num layers=2, Input size=1, Hidden size=50, Learning rate=0.001, Output size=1, Iterations=100, Batch size=32.
Bi-LSTM	Layers = 50, 50, 50, 8 units, Activation='RELU', Iterations=100, Batch size=32
Bi-GRU	Layers = 50, 50, 50, 8 units, Activation='RELU', Iterations=100, Batch size=32
Stacked LSTM	Layers = 50, 50, 50, 50, 8, 1 unit, Activation='RELU', Activation='Sigmoid' for last layer, Optimizer='ADAM', Iterations=100, Batch size=32
ACNN-OBDLSTM	Filters=64, Kernel size=2, Unit=50, Kernel initializer='orthogonal', Iterations=100, Batch size=32

4.2.2 Statistical Summary of Data

The dataset for TOP prices in the Azadpur market, Delhi, shows challenges such as outliers, fluctuations, irregularity, and non-linearity. Extreme values can skew the overall dispersal of data, and the wavering and non-symmetrical characteristics of the data complicate traditional forecasting methods. A high span of price alterations suggests non-linear patterns and complexity that are not well-suited for linear models. Additionally, sudden extreme price shifts introduce further non-linearity, making deep learning models necessary for accurate forecasting of TOP crop prices. Table 4.3 describes the statistics and distribution of TOP crop prices.

Table 4.3. Descriptive Statistics of TOP crop prices dataset.

Parameter	**Tomato (N=2751) (Rs./quintal)**	**Onion (N=2531) (Rs./quintal)**	**Potato (N=2841) (Rs./quintal)**
Mean	1626.58	1446.92	1076.47
Standard Deviations	942.74	771.84	540.04
Minimum Data	243.00	555.00	335.00
First Quartile	958.50	858.00	666.00
Third Quartile	2119.50	1750.00	1388.00
Maximum Data	8067.00	4625.00	3850.00

4.2.3 Comparative Analysis

The Agmarknet dataset, which covered the years 2014 through 2024, contained daily modal prices that were used to train and test the models. The dataset included 2,751 data points for tomatoes, 2,531 data points for onions, and 2,841 data points for potatoes. The dataset was split in half: 80% was used to train the models, while the remaining 20% was used to assess how well the models predicted the data [19].
From Tables 4.4, 4.5 and 4.6, we can see that LSTM works best for the TOP crop prices dataset.
Fig. 4 illustrates the performance of models using bar chart for all deep learning models used on TOP commodity in terms of MAE, RMSE, MAPE and R-squared metrics.

Table 4.4. Models Performance on Tomato Crop Prices

Models/Metrics	**MAE**	**RMSE**	**MAPE(%)**	**R-squared**
LSTM	**100.41**	**220.37**	**4.05**	**0.92**

RNN	112.84	219.55	4.57	0.92
GRU	110.46	239.01	4.34	0.9
TCN	204.61	304.79	9.23	0.84
CNN-LSTM	126.25	248.13	5.1	0.9
PECAD	108.78	246.19	4.22	0.9
Bi-LSTM	110.03	226.58	4.47	0.91
Bi-GRU	108.04	242.99	4.23	0.9
Stacked LSTM	102.87	220.11	4.17	0.92
ACNN-OBDLSTM	122.86	236.68	5.07	0.91

Table 4.5. Models Performance on Onion Crop Prices

Models/Metrics	**MAE**	**RMSE**	**MAPE(%)**	**R-squared**
LSTM	**88.83**	**225.67**	**3.9**	**0.9**
RNN	98.81	225.9	4.43	0.9
GRU	106.09	228.33	4.8	0.9
TCN	110.21	233.69	5.01	0.89
CNN-LSTM	110.23	232.87	5.04	0.89
PECAD	98.7	225.85	4.47	0.9
Bi-LSTM	96.64	225.89	4.43	0.9
Bi-GRU	103.15	226.53	4.69	0.9
Stacked LSTM	101.66	230.91	4.32	0.89
ACNN-OBDLSTM	115.34	232.5	5.44	0.89

Table 4.6. Models Performance on Potato Crop Prices

Models/Metrics	**MAE**	**RMSE**	**MAPE(%)**	**R-squared**

LSTM	**18.81**	**47.56**	**1.64**	**0.98**
RNN	44.03	64.1	3.86	0.97
GRU	34.88	55.72	2.9	0.98
TCN	44.56	67.07	4.06	0.97
CNN-LSTM	27.59	54.65	2.36	0.98
PECAD	25.74	48.56	2.16	0.98
Bi-LSTM	26.99	51.2	2.27	0.98
Bi-GRU	26.49	51.18	2.52	0.98
Stacked LSTM	37.19	59.55	3.38	0.98
ACNN-OBDLSTM	23	50.28	1.92	0.98

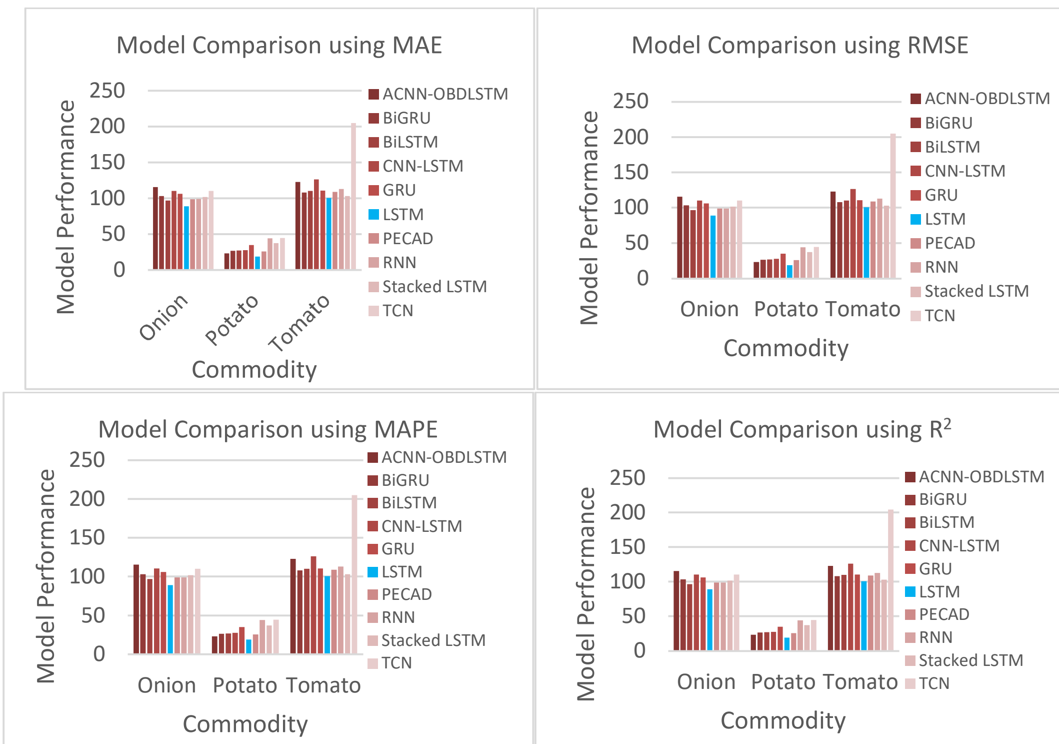


Fig. 4.1. Bar Chart for Comparison of Deep Learning Models for TOP Commodity using MAE, RMSE, MAPE and R^2 performance metrics.

4.2.4 Model Performance Graphs

- **LSTM**

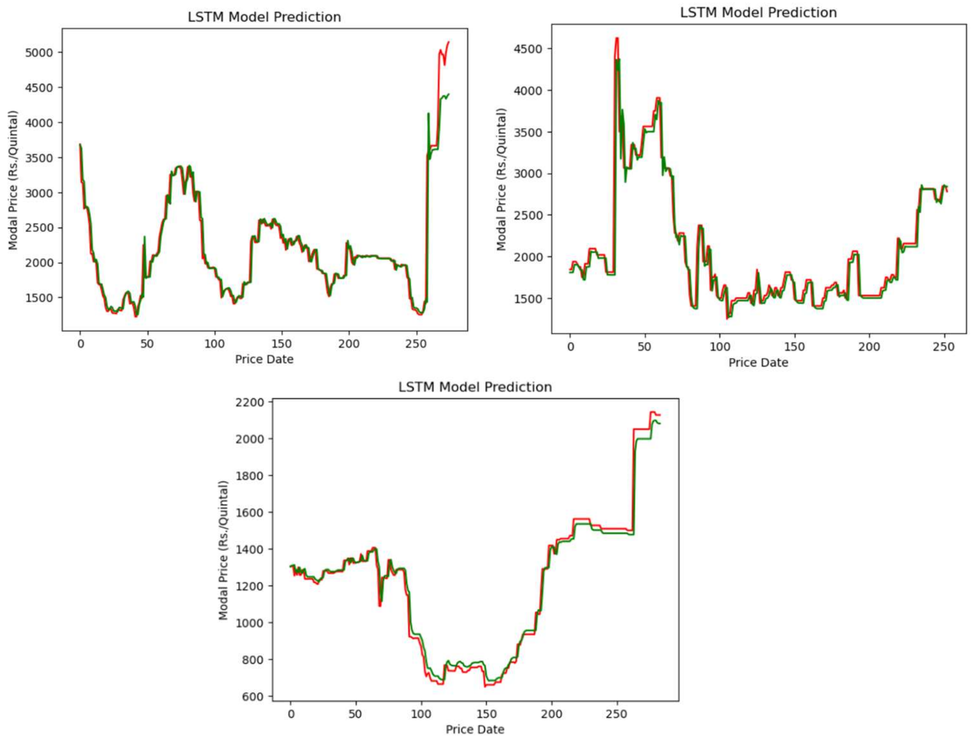
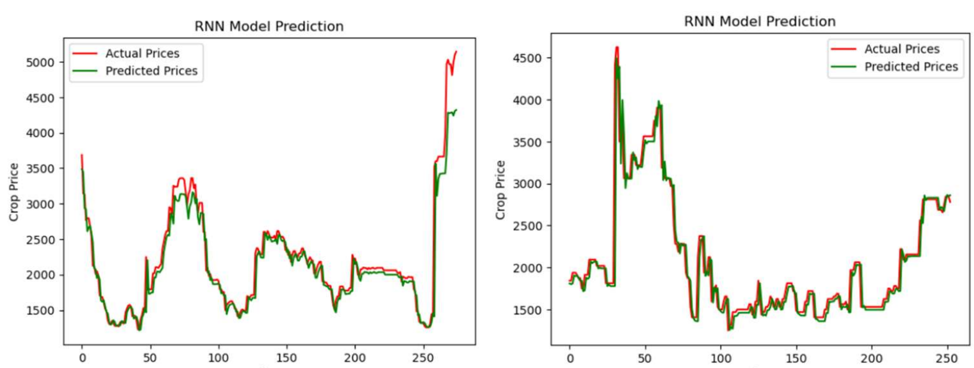


Fig. 4.2. Line Chart on Performance of LSTM for (a) Tomato, (b) Onion and (c) Potato

- **RNN**



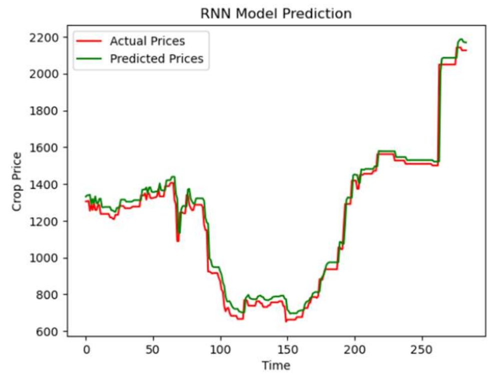


Fig. 4.3. Line Chart on Performance of RNN for (a) Tomato, (b) Onion and (c) Potato

- **GRU**

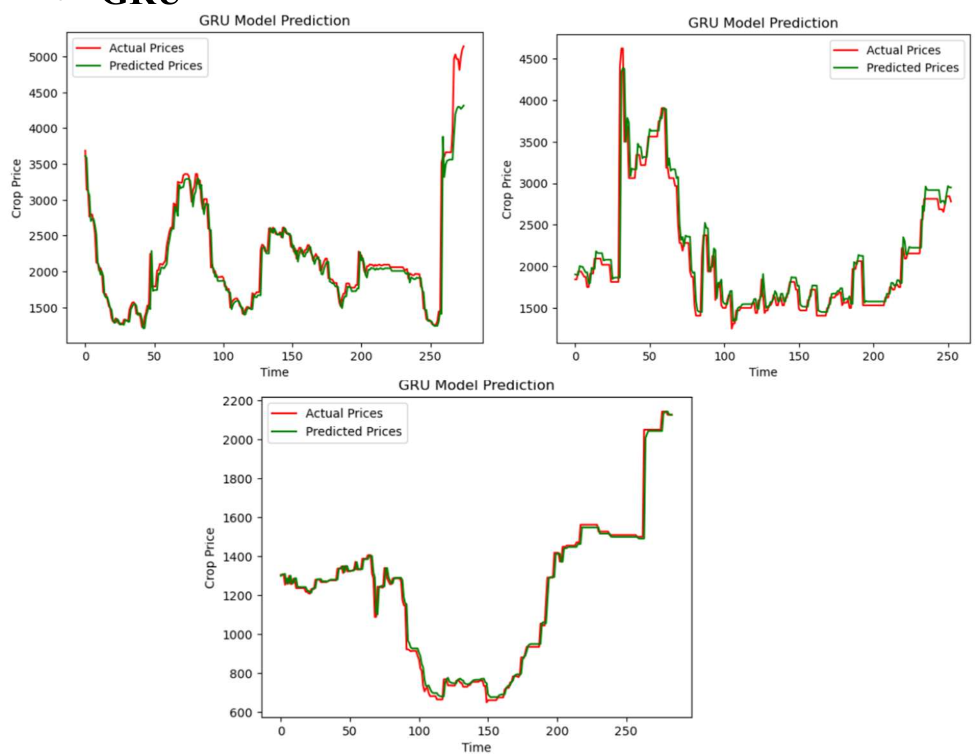


Fig. 4.4. Line Chart on Performance of GRU for (a) Tomato, (b) Onion and (c) Potato

- **TCN**

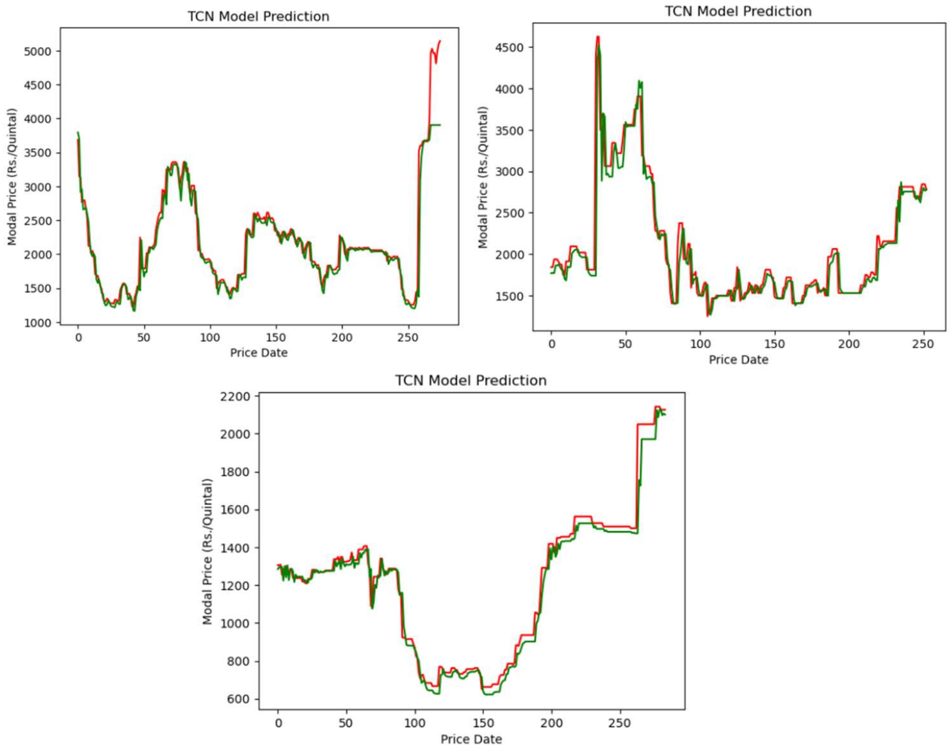


Fig. 4.5. Line Chart on Performance of TCN for (a) Tomato, (b) Onion and (c) Potato

- **CNN-LSTM**

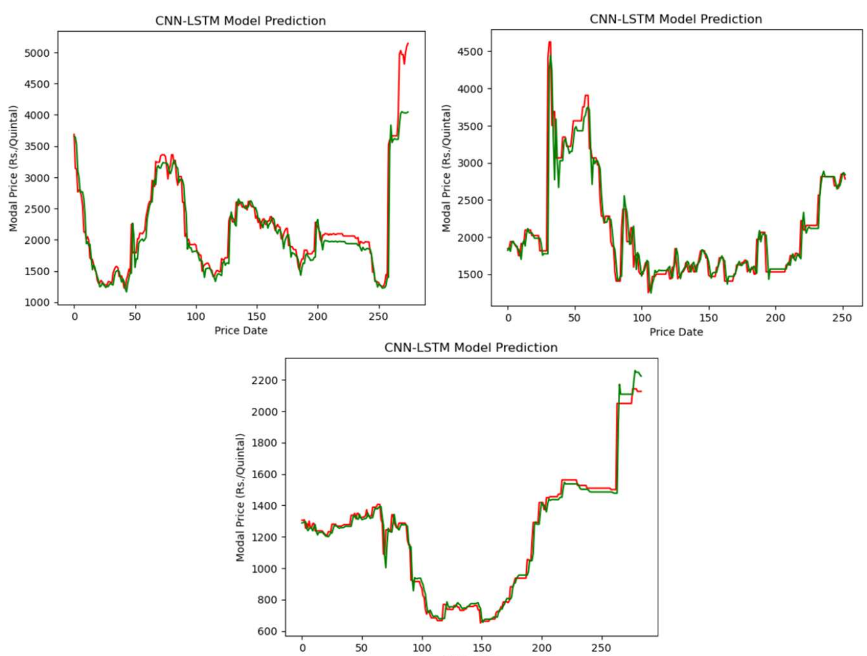


Fig. 4.6. Line Chart on Performance of CNN-LSTM for (a) Tomato, (b) Onion and (c) Potato

- **PECAD**

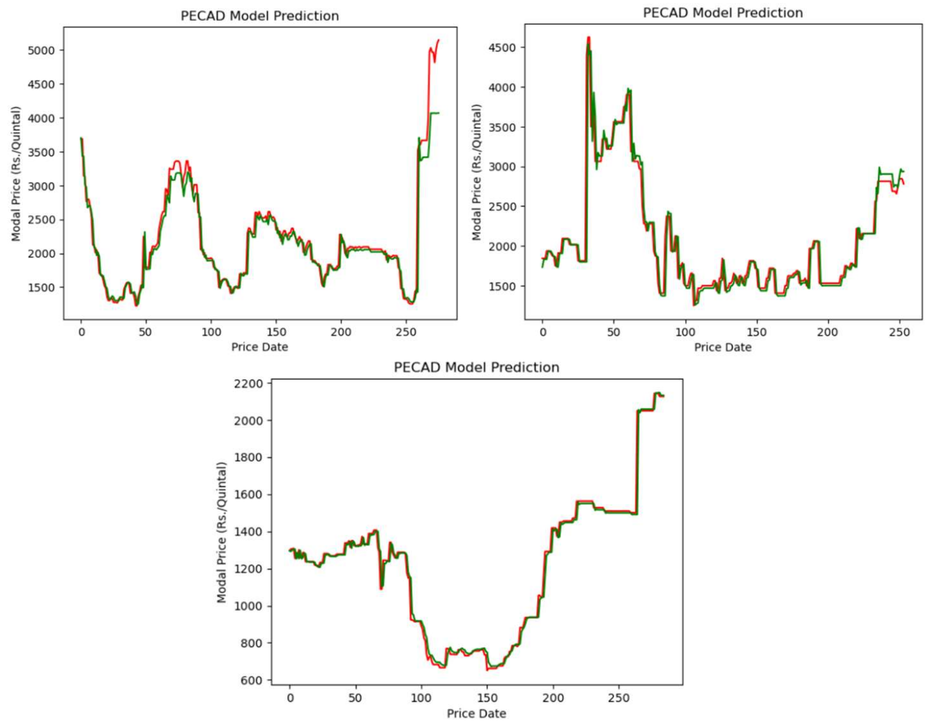
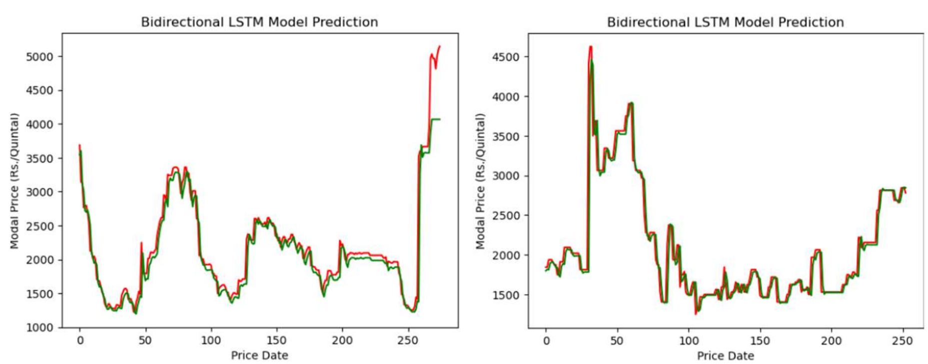


Fig. 4.7. Line Chart on Performance of PECAD for (a) Tomato, (b) Onion and (c) Potato

- **Bi-LSTM**



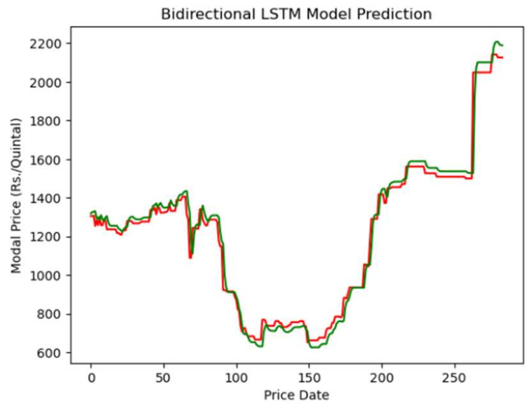


Fig. 4.8. Line Chart on Performance of Bi-LSTM for (a) Tomato, (b) Onion and (c) Potato

- **Bi-GRU**

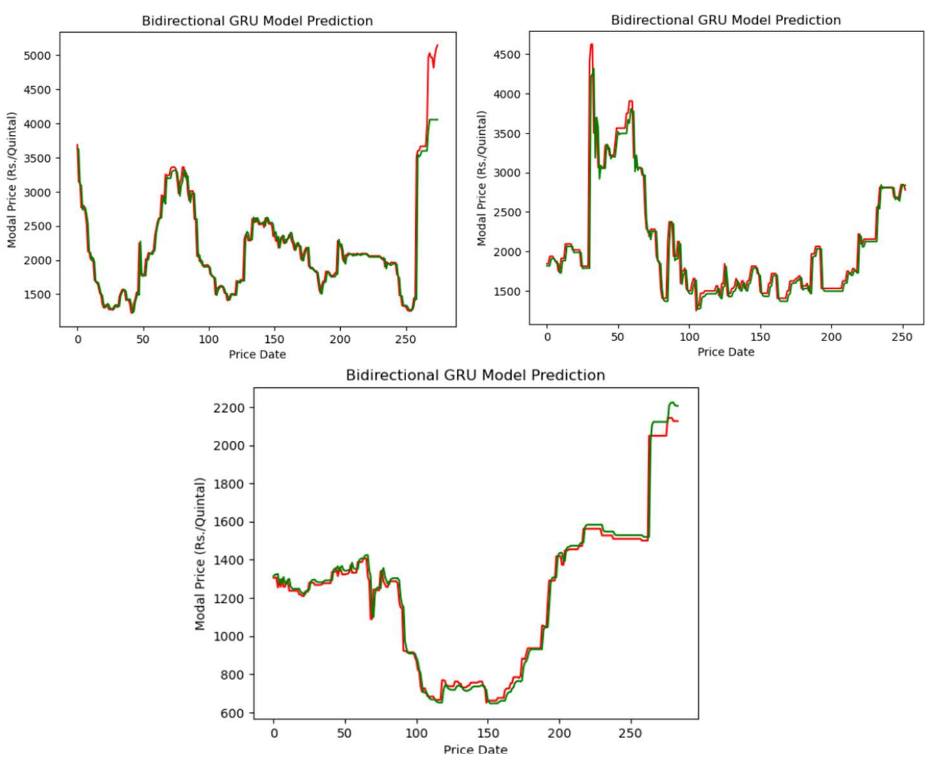


Fig. 4.9. Line Chart on Performance of Bi-GRU for (a) Tomato, (b) Onion and (c) Potato

- **Stacked LSTM**

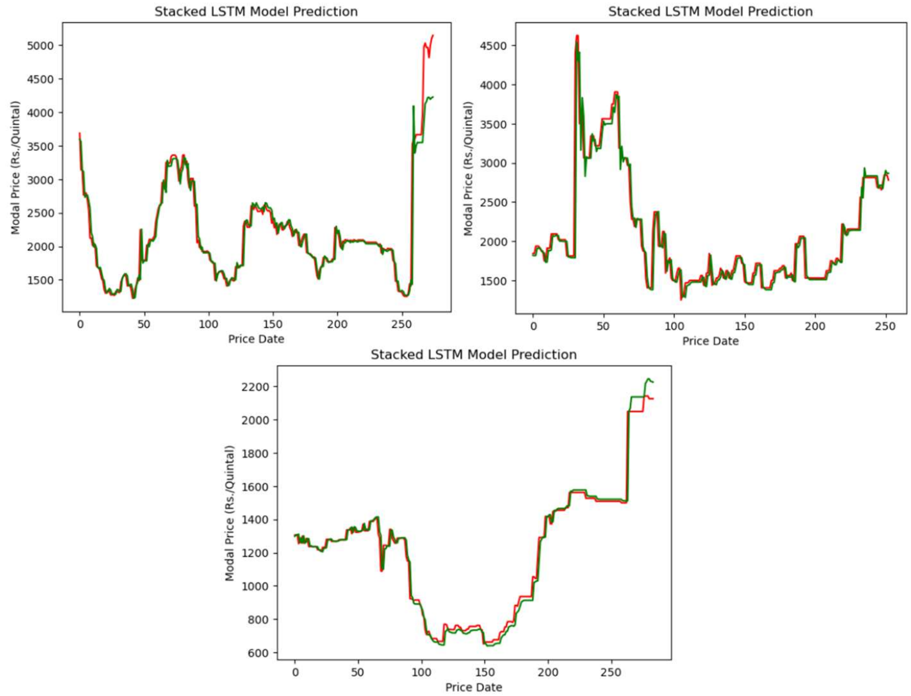


Fig. 4.10. Line Chart on Performance of Stacked LSTM for (a) Tomato, (b) Onion and (c) Potato

- ## ACNN-OBDLSTM

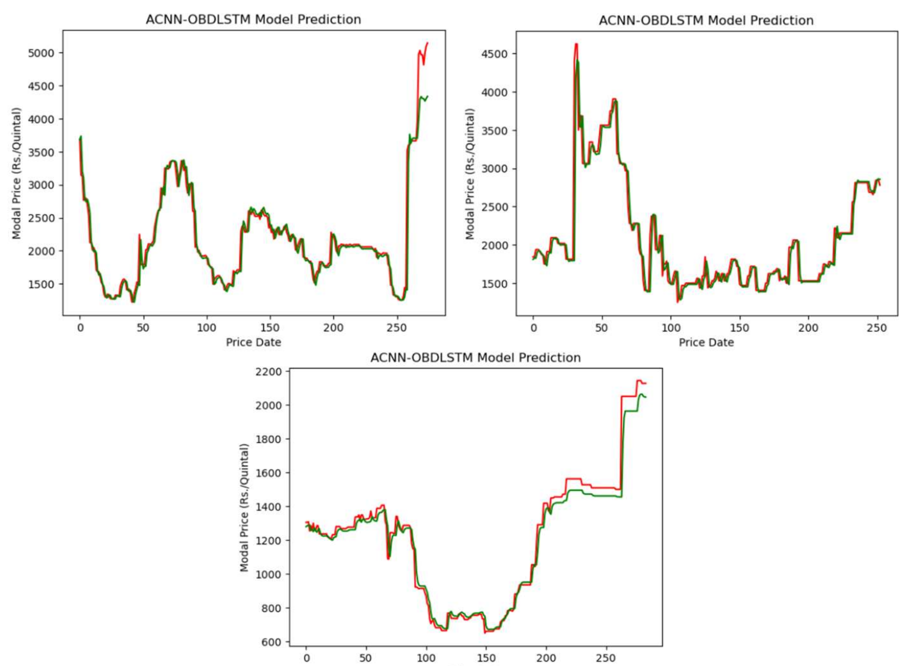


Fig. 4.11. Line Chart on Performance of ACNN-OBDLSTM for (a) Tomato, (b) Onion and (c) Potato

4.3 Discussion

The evaluation's findings showed that the LSTM model had the best prediction with the highest accuracy for the Tomato, Onion, and Potato prices, The LSTM attained the lowest combination of RMSE, MAPE, MAE, and the highest R-squared values when tested on the dataset. Fig. 3 displays the framework of the LSTM model which performs comparatively better than other proposed models.
The analysis also uncovered a harmonious yearly pattern of TOP prices where the commodity prices reached their lowest in April, May, and January, respectively. Farmers can arrange their production and harvesting plans precisely at times of higher prices with the help of this insightful information to ease up the market prices of crops for the population of India and gain profit for themselves. Moreover, this awareness can be used by traders and market committees to create more successful plans and make better decisions.

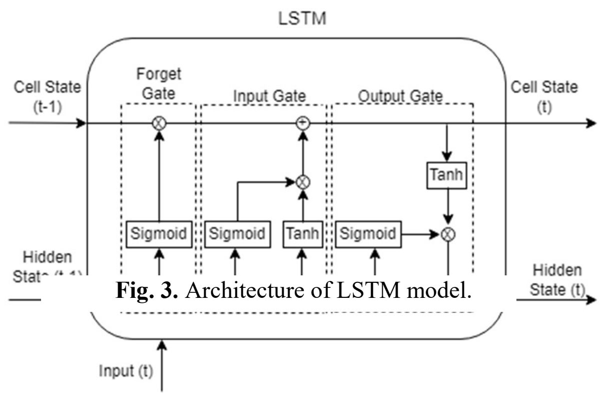


Fig. 4.12. Architecture of LSTM

Chapter 5
CONCLUSION and FUTURE SCOPE

To examine AI's use in agricultural price forecasting, this study brings together the findings from many recent articles and a practical analysis of a case study. The review included 17 papers from 2021 to 2024 which found that the transpiring patterns in forecasting methods using DL systems. When tested, LSTM networks, Transformers and Graph Neural Networks proved to be more accurate than ARIMA and panel data regression. DL recognizes complicated, curved relationships and detects lasting connections in records from the field.

For verification, we applied an LSTM model to foresee the prices for TOP at Azadpur Market in Delhi. Data was taken from Agmarknet and the model was trained using this information without much preparation, except for replacing outliers with nearby values and scaling the data up to achieve good results. Even without data manipulation, the model still managed to detect consistent increases in tomato prices every April, onion prices every May and potato prices every January. By using MAE, RMSE, MAPE and R-squared, it was shown that LSTM performed reliably, meeting the expectations for forecasting problems.

The promising model for crop price forecasting is LSTM. Well-developed and constantly being applied, they can help farmers, markets and policymakers take better decisions thanks to data collection.

If further data sources are used, it can improve predictions for the future. Examining weather, rain, temperature, transport hold-ups and the demand for goods can help explain why prices change. Introducing these into the model may increase the model's accuracy with reality. It is also possible to use transfer learning to transfer models from one variety or area to another without spending much time or money. With sensors and data from IoT, predictions can happen faster and be adjusted easily, even if prediction is done on the edge or in the cloud. As a final benefit, federated learning helps in training models using various data sources while keeping data private in situations where different Agri-systems are not connected.

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APPENDIX A

A.1 LIST OF PUBLICATION

1. Srijan Srivastava, Dr. Sonika Dahiya, Priyanka Arora (2025). Advanced Deep Learning Models for Forecasting Tomato, Onion, and Potato Prices: A Comparative Study. **[Scopus Indexed] [Accepted]**

2. Srijan Srivastava & Dr. Sonika Dahiya (2025). A Review Paper on the study of Deep Learning and Machine Learning Models used in Forecasting Indian Crop Prices. **[Scopus Indexed] [Accepted]**

A.2 PAPER ACCEPTANCE PROOF

A.2.1 1st Conference Acceptance Proof:

5/19/25, 4:12 PM Gmail - Reg : Registration Reminder- ICICC 2025 : Paper Notification for Paper ID 261

Gmail **Srijan Srivastava <srijan2705@gmail.com>**

Reg : Registration Reminder- ICICC 2025 : Paper Notification for Paper ID 261
1 message

ICICC 2025 <icicc.ui@gmail.com> 1 November 2024 at 14:19
To: Srijan <srijan2705@gmail.com>

International Conference on Innovative Computing and Communication (ICICC) – A Flagship Conference

Dear Author(s),

Greetings from ICICC 2025!

We congratulate you that your paper with submission ID **261** has been accepted for publication in the Springer LNNS series [Indexing: SCOPUS, INSPEC, WTI Frankfurt eG, zbMATH, SCImago; All books published in the series are submitted for consideration in Web of Science].

To secure your spot at this highly anticipated event and to opt for early bird registeration, we urge you to complete your registeration on or before 05th November 2024. We have extended the deadline only for early bird registration till 5th November 2024.

Pay registration fees via online portal:

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Research Scholar/Student/Academician/Industrial Participant (India/ Outside India):
https://icicc-conf.com/registrations)

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A.2.2 2nd Conference Acceptance Proof:

5/19/25, 4:17 PM Gmail - ICDAM 2025: Registration Reminder for Paper ID 1128

Gmail Srijan Srivastava <srijan2705@gmail.com>

ICDAM 2025: Registration Reminder for Paper ID 1128
1 message

ICDAM 2025 <icdam.conf@gmail.com> 5 May 2025 at 16:53
To: Srijan <srijan2705@gmail.com>

NOTE: Due to several requests, we are providing the last chance for the early bird registration deadline. It will not be extended. You can do the registration by 10th May 2025. On website, it is 30th April 2025

6th International Conference on Data Analytics & Management (ICDAM-2025)!

Dear **Author(s),**

We congratulate you that your paper with submission ID **1128** and Paper Title **'A Review Paper on the study of Deep Learning and Machine Learning Models used in Forecasting Indian Crop Prices'** has been accepted for publication in the **Springer LNNS series** [Indexing: SCOPUS, INSPEC, WTI Frankfurt eG, zbMATH, SCImago; All books published in the series are submitted for consideration in Web of Science].

We want to give you urgent information and let you know that we have very few slots left. Once they are filled, we cannot accommodate any further registrations. To secure your spot at this highly anticipated event, we urge you to complete your registration without delay before 10th May 2025. Due to a number of requests, we have extended the early bird registration deadline by 10th May 2025

If you are already registered, please ignore this email. If you have not shared the screenshot of the payment, kindly share it. We will mark your paper under the registered paper category.

You are requested to do the registration as soon as possible and submit the following documents to icdam.conf@gmail.com at the earliest.
1. Final Camera-Ready Copy (CRC) as per the springer format. (See https://icdam-conf.com/downloads)
2. Copy of e-receipt of registration fees. (For Registration, see https://icdam-conf.com/registrations)
3. The final revised copy of your paper should also be uploaded via Microsoft CMT.

Note : **Standard Paper size – 10-12 pages. Over length of more than 12 pages, paper charges USD 20 per extra page**

Pay registration fees via online portal:
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A.3 INDEXING OF CONFERENCE PROOF

A.3.1 1ST Conference

9th INTERNATIONAL CONFERENCE ON INNOVATIVE COMPUTING AND COMMUNICATION (ICICC-2026)

ICICC
INTERNATIONAL CONFERENCE ON INNOVATIVE COMPUTING AND COMMUNICATION

ORGANISED BY:
SHAHEED SUKHDEV COLLEGE OF BUSINESS STUDIES, UNIVERSITY OF DELHI, NEW DELHI
IN ASSOCIATION WITH
NATIONAL INSTITUTE OF TECHNOLOGY PATNA & UNIVERSITY OF VALLADOLID SPAIN

6th-7th FEBRUARY 2026

Springer

ICICC 2025

The eighth version of the International Conference in Innovative Computing and Communication (ICICC-2025) was organized at Shaheed Sukhdev College of Business Studies in association with the National Institute of Technology Patna and the University of Valladolid Spain, on 14-15 February 2025 at New Delhi, India. ICICC-2025 received 2000 papers from approximately 6000 plus authors and a total of 400 papers were accepted with an acceptance ratio of 20%. All accepted papers were published in Springer's Lecture Notes on Networks and Systems, a Scopus-indexed series. A total of 750 participants attended the conference including authors, keynotes, delegates, academicians, and industry experts. ICICC-2025 received papers from 35 countries. ICICC-2025 was organized in hybrid mode.

Important Dates

A.3.2 2nd Conference

5/19/25, 2:30 PM ICDAM | International Conference on Data Analytics and Management

6th International Conference on Data Analytics & Management (ICDAM-2025)

ICDAM-2025 Theme: Data Analytics with Computer Networks

Organized By: London Metropolitan University, London, UK (Venue Partner)

in association with

WSG University, Bydgoszcz Poland, Europe

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Portalegre Polytechnic University, Portugal, Europe

&

SGGW Management Institute

Date: 13th - 15th June, 2025

Springer LNNS Approved Conference (Indexed in Scopus, EI, WoS and Many More)

https://icdam-conf.com 1/13

A.4 CONFERENCE CERTIFICATE

ICICC-2025

INTERNATIONAL CONFERENCE ON INNOVATIVE COMPUTING AND COMMUNICATION (ICICC-2025)

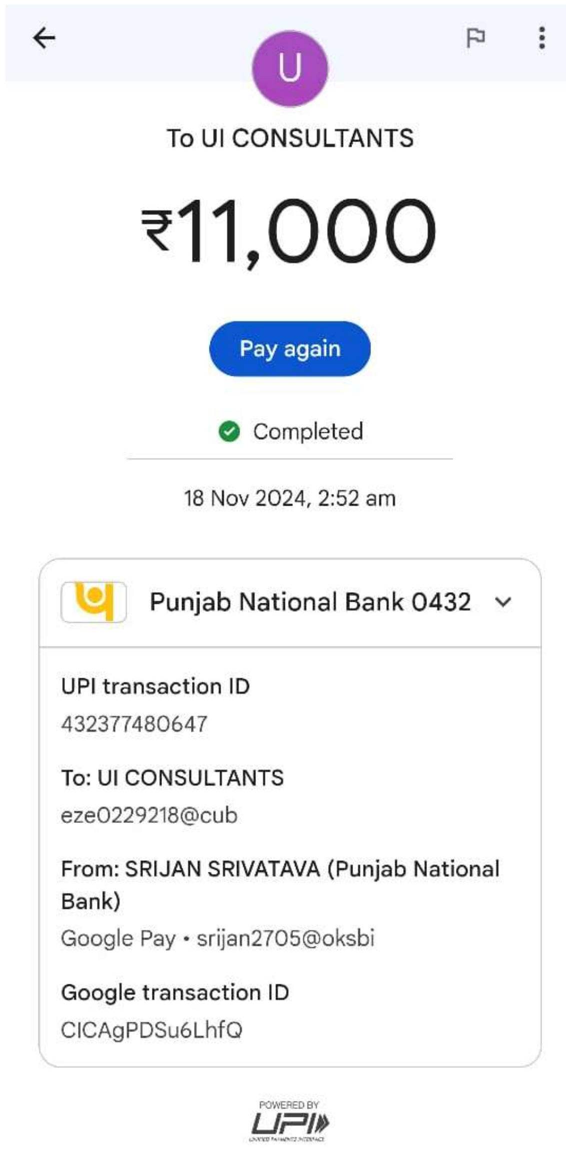
Certificate

This is to certify that **Prof. / Dr. / Mr. / Ms. Srijan Srivastava** is a presenter/co-author of the paper titled **Advanced Deep Learning Models for Forecasting Tomato, Onion, and Potato Prices: A Comparative Study** in the **8th International Conference on Innovative Computing and Communication (ICICC-2025)**, organized by Shaheed Sukhdev College of Business Studies, University of Delhi, New Delhi, India in association with the National Institute of Technology Patna, India and the University of Valladolid, Spain on **14th-15th February 2025**.

Poonam Verma	**Prabhat Kumar**	**A K Singh**
Principal, SSCBS, University of Delhi, New Delhi	General Chair National Institute of Technology, Patna	Technical Program Chair National Institute of Technology, Kurukshetra

A.5 CONFERENCE PAPER REGISTRATION RECEIPT

A.5.1 1st Conference Receipt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