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Onion Price Forecasting using Machine Learning Models Market of South Punjab

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Abstract

Price plays a crucial role in financial activities, with unexpected fluctuations often signaling market instability. In today's market, machine learning offers a variety of techniques to forecast commodity prices, helping to manage such instability. This paper explores the application of machine learning methods for forecasting onion prices, using data attained from the Ministry of Agriculture, South Punjab, Pakistan. We applied machine learning algorithms such as Linear Regression, SARIMA, LSTM, SVR, and Random Forest Regression to make forecasts. We then evaluated and compared the performance of these techniques to determine which provides the highest accuracy. Our findings indicate that all the methods used to determine which offer high accuracy and suggest that all the techniques produced similar results. Using these methods, we aim to forecast onion prices into three categories: low (preferable), medium (economical), and high (expensive).

Keywords: *Onion Market Price, Price Prediction, Forecasting Models, Regression Analysis, Predictive Modeling.*

1. Introduction

Onions are widely consumed as a staple in our daily meals. Across the Southern region of Punjab, Pakistan, approximately 756,500 metric tons of onions are needed annually, and 20,748 metric tons are required daily. Unforeseen changes in onion prices have become an important concern in the region's economic conditions. In late 2023, in South Punjab, Pakistan,

a dramatic change was observed in onion prices. During 2023, the average Onion market price was Rs. 120 per kg on the 1st of January, but in December, it was Rs. 280 per unit weight (kg). This change elaborates considerable attention for its abnormal trend. Its primary production and distribution significantly affect the livelihoods of local farmers and traders. The analysis publicized that price variations were significantly high such prices are unreasonable for the deprived population of South Punjab. With time, onion became essential in the local diet and used in a variety of traditional dishes. Onion is a fundamental cash crop for farmers in South Punjab. Price forecasting is demanding because of messy nature and data inconsistency.

In the modern epoch of artificial intelligence, machines are validating intelligent capabilities. From this perspective, machine learning models offer practical and viable solutions by using data driven approaches to forecast onion prices with high precision. This article assesses the use of machine learning models to forecast onion prices in South Punjab market, emphasizing the potential benefits and challenges of this innovative approach.

Hussein et al. [1] To develop an efficient system for accurate and reliable stock market predictions, they utilized Artificial Neural Networks (ANN). Predictive analysis uses historical data to predict future events, and the predicted values support decision making and planning in areas such as marketing and production. Similarly, prediction can be applied to agricultural decision making, for example, Swarup and Kushwaha. [2] Provided and analyzed daily price data from markets and used the traditional GARCH method to compute daily conditional volatilities, which were then used to forecast instabilities for the next 10, 15, and 21 days, with their accuracy compared against the AI model.

Furthermore, predictions can be applied to estimate the selling prices of agricultural commodities. Since our work is prediction-oriented, we employed supervised learning algorithms to generate forecasts. The Machine Learning techniques mentioned are used to forecast onion prices, which is the main objective of our work.

This paper is organized as follows. Section 2 presents a review of related work. Section 3 describes the proposed methodology. Section 4 discusses the expected results and compares the outcomes obtained from different Machine Learning techniques for onion price forecasting. Finally, the paper concluded with a conclusion containing future directions.

2. Review of Work

Several studies have investigated the use of Machine Learning for forecasting, particularly in predicting the commodity price to address market instability. These studies have focused on

various problems and applied Machine Learning to address the associated challenges.

Previous research on the supply and demand prediction for vegetable price forecasting has utilized the Seasonal-Trend-Loess (STL) preprocessing method combined with Long Short-Term Memory (LSTM) deep learning algorithm, which, when applied to the Korean agricultural market, achieved forecast accuracies of 92.06% for Chinese cabbages and 88.74% for radishes, highlighting its potential for improving supply-demand adjustments and policy development to stabilize vegetable prices despite meteorological fluctuations [3].

This study compares regression and Long Short-Term Memory (LSTM) models for estimation vegetable prices using variables[4] such as crop type nutrient value minimum support price, variety and location, with findings showed that LSTM offered superior accuracy and fit based on standard metrics. The financial sector has proven to be one of the most promising fields for the application of machine learning. Inspired by this, our study applies Machine Learning (ML) techniques to the collected onion price data for forecasting purposes. To make the dataset more manageable different feature selection methods can be employed. However, forecasting onion price is a complex task, multiple factors influence the predictions Machine Learning provides advance approaches for this purpose.

To find price Hasen et al. [5] evaluates many several machine learning algorithms for predictating onion prices for Bangladeshi data,find compareable performance in classifying prices as low, mid, high. Bini and Methew [6] presented data mining based system that has utilized clustering methods like K-means and EN,along with multiple regression,to identify profitable companies and predict future stock prices.

Nam,Kuk Hyun and Choe. [7] used ARDL modeling with data from Korean agencies to predict 215 onion cultivation areas, yields, and wholesale prices,estimated prices to have exceeded 1000 won after August. Yuan et al. [8] In 2018, this study developed novel Machine Learning strategies with optimal lag time selection to enhance the forecasting accuracy agricultural commodity prices in Malaysia, to enhance plantation planning and address price volatility.

Guo et al. [9] introduced the attLSTM-ARIMA-BP model,which combines multiple algorithms to predict corn prices in Sichuan province,offering enhanced accuracy and robustness over seven other models,making it highly effective for forecasting prices in complex environments.

Adil et al [10] the study has estimated future proections for onion area,production and consumption in Punjab,Pakistan, using the ARIMA model, and has identified a significant supply-demand gap by 2025, emphasizing the need for targeted research,development and policy measures.Ray et al. [11] developed a Random Forest Convolutional Neural Network (RF-CNN) model to forecast the volatile potato price measure demonstrating that it significantly outperformed traditional statistical models and other machine learning models in terms of error accuracy. Gotze et al. [12] built the forecasing model for CAT (catastrophe bonds) premia in the secondary market and found that Random Forest provides the most accurate predictions.They were significantly more accurate from Linear Regression and other machine learning models.

Related studies have also been conducted in the agriculture domain to predict production using SVM approaches. Algorithms and correlatin matrix were used.The author Hue et al.[13] Applied Support vector Machines to predict stock market performance,demonstrating that SVM effectively analyzed the relationship between selected company-specific and macroeconomic factors, confirming its strength as a predictive tool in the financial market.The results was measured.

Finally, the proposed model accuracy was measured using evaluation metrics.In contrast to prior research, we used Machine Learning (ML) approaches to collect or normalize data and determine precision.

3. Methodology

The methodology of our study involves,data collection,data analysis, algorithm implementation and evaluation, as illustrated in Fig.1.To achieve our desired results,we followed these steps.

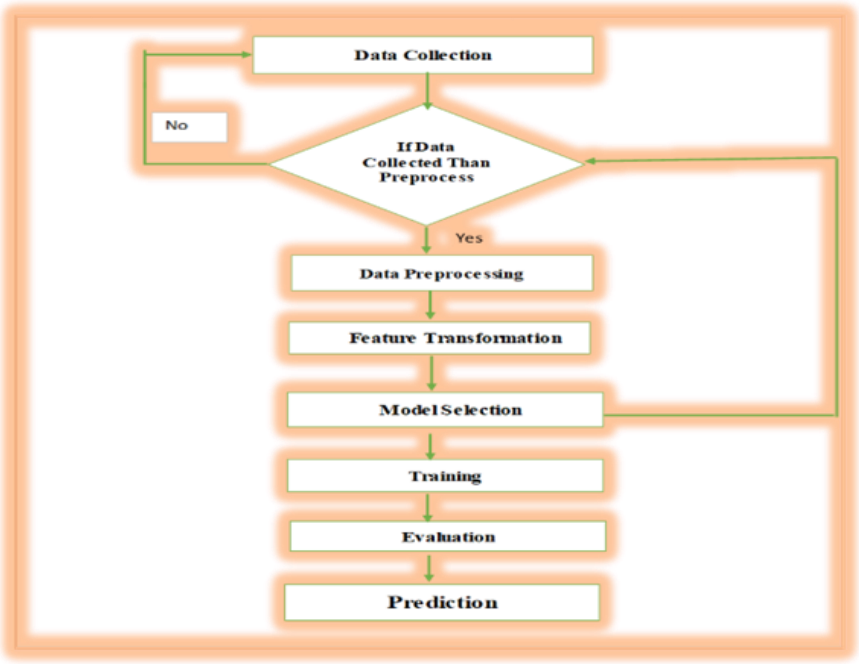

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Fig. 1: Methodological Framework

Fig.1 demonstrates the methodology used to achieve our results.The process was carried out in the following steps.

3.1. Data Collection

We obtaineed the necessary data from the Ministry of Agriculture website, gathering daily samples or records of onion prices.Daily price data of onion for the period 1st January, 2020 to 31st March, 2024 have been collected from different markets of South Punjab, Pakistan. This dataset consisted of numerical, unstructured, time series data, which required further processing in the subsequent steps.

3.2. Data Analysis

Prior to applying the algorithms, the data was structured and the important features selected such as year, month, date,daily demand metric tons, daily supply metric tons, price and price change drieved attribute based on price.Our collected data set initially contained unwanted and unclean data that needed to be removed before proceeding with algorithm implementation.To clean the data and creat the desired data frame,We utilized the popular ML tool pandas.

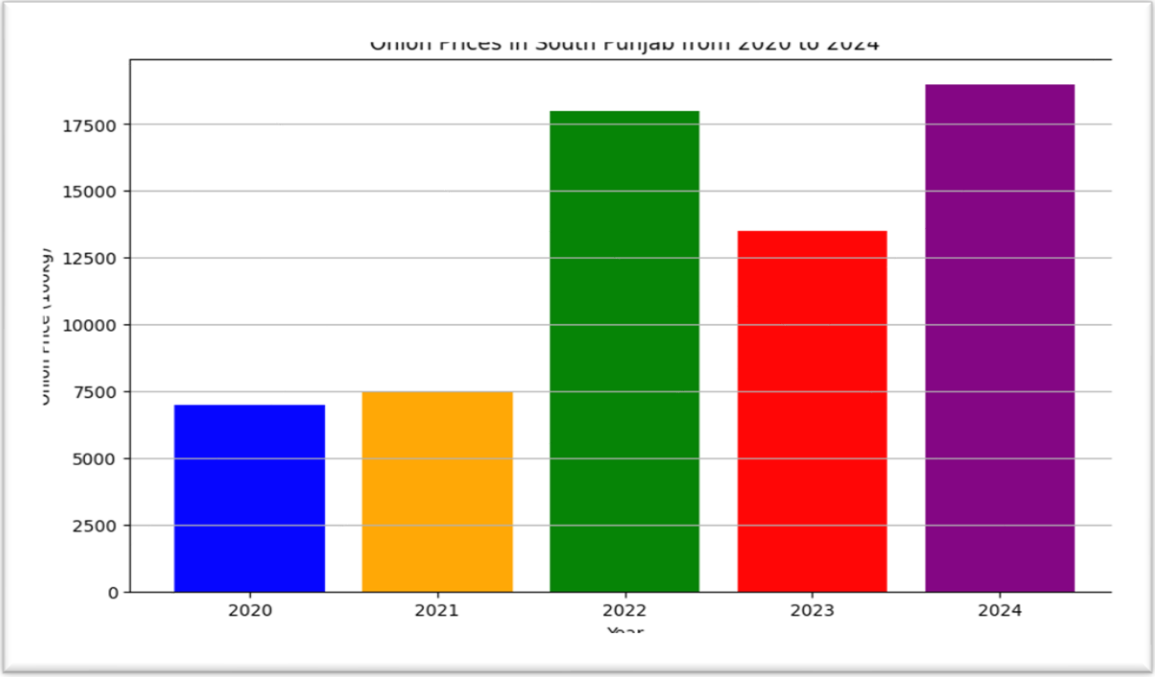

Fig. 2: Yearly price range

Fig 2: x-axis representing years and y-axis representing onion price. We plotted bar chart, each bar represents the onion price for a specific year.The height of bar corresponds to the price of 100kg of onions.Bars colored differently to distinguish each year.Grid lines presents to help gauge the height of each bar relative to the y-axis.From the Fig 2 we can easly determine significant fluctuations in onion prices from 2020 to 2024, with a sharp spike in 2022 indicating market instability, and varying colors aids in visual comparison of yearly price trend for better decision making.

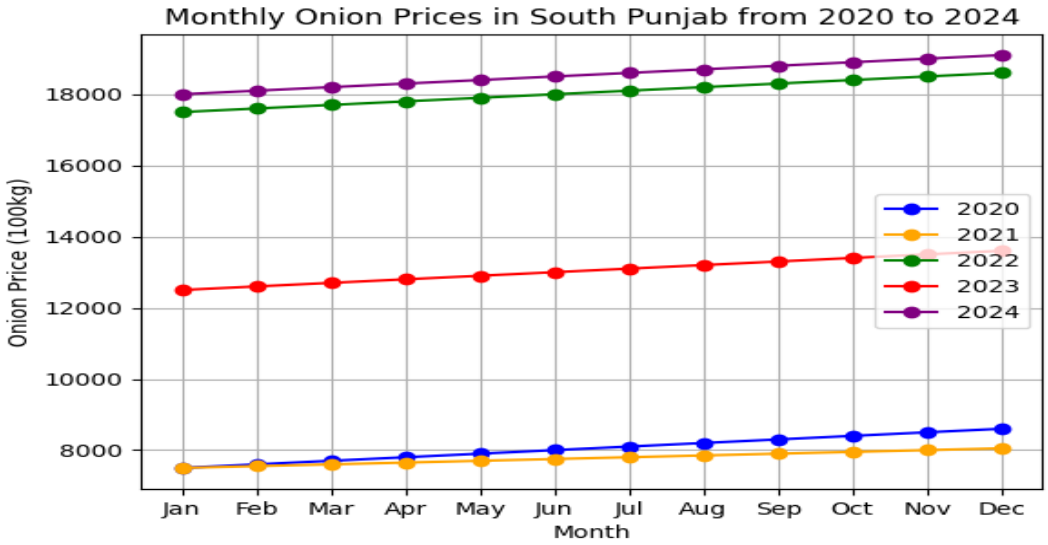

Fig. 3: Monthly onion price fluctuations

Fig. 3 shows a line graph with months on the x-axis and the corresponding onion prices on the y-axis. Visually representing the price fluctuations. From this graph we gained insights through detailed data analysis, observing trends in onion prices. It was observed that onion prices were low at the start of year and would be high at the end of the year and vice versa. This trend persisted in previous years as well. Recognizing this pattern, we introduced a new parameter, which enhanced the accuracy of our onion price predictions.

3.3. Algorithm Implementation:

We first categorized the onion prices then applied supervised learning techniques using specific algorithms. Upon completion of the data evaluation, the data were preprocessed for implementation of algorithms. Each approach or model was applied in sequence, and their performance was assessed, eventually estimating their precision. The algorithms based on Machine Learning (ML) was used for onion price forecasting comprised Linear Regression, SARIMA, LSTM, SVR and Random Forest Model.

3.3.1. Linear Regression

A statistical, supervised machine learning model used to develop a linear relationship between the dependent variable (Y) and the independent variable (X). The model compares the actual value of the target (Y) with its predicted value. The difference between actual and predicted values are called residuals, residual measure the error of one observation.

3.3.2. SARIMA

Seasonal Autoregressive Integrated Moving Average (SARIMA) is a time series forecasting method used for both trends and seasonal patterns for onion price data.

3.3.3. SVR, LSTM, Random Forest

Support Vector Regression (SVR) algorithm that estimates subsequent values by recognizing the best fit hyperplane (minimize the distance between the data points), reducing the estimation error.

LSTM (Long Short-Term Memory) is a type of recurrent neural network (RNN) particularly developed to manage ordered data and capture the long-term dependencies.

Random Forest: A Random Forest is an ensemble machine learning algorithm that builds multiple decision trees to improve accuracy and proficiency in both regression and classification.

3.3.4. Evaluation

At this stage, the dataset is prepared, and we implement five different models (Machine

Learning Algorithms). Algorithms produced consequences (results). The findings are close to our prospects. In the experimental results section, we will further analyze and refine these results.

4. Experiment Results

The selected algorithms were applied to the prepared dataset, their performance was evaluated, and the results were recorded in an accurate table for comparison.

Table 1: Algorithms Accuracy Rate

Data Usage Rate	Algorithms				
	Linear Regression	**SARIMA**	**LSTM**	**SVR**	**Random Forest**
50%	75.2%	73.4%	80.5%	78.1%	83.0%
60%	78.5%	76.3%	82.8%	81.0%	85.2%
70%	84.6%	83.9%	89.0%	87.5%	90.8%
80%	86.1%	85.4%	90.3%	89.1%	92.3%
90%	88.0%	87.3%	91.7%	91.0%	93.7%

Table 1 presents the accuracy of models for forecasting Onion prices using varying proportions of training data. The accuracy rate represents each model's performance as training data increases from 50% to 90%. The subsequent columns display the accuracy of five models. The yellow boxes highlight the lowest accuracy achieved by each model, while the green boxes highlight the highest accuracy achieved by each corresponding model (Hegde et al.[14] Designed a machine learning based model for forecasting commodity prices and a Kannada voice bot to help farmers in Karnataka access market information and price forecasts in their local language, addressing the challenges of technology awareness and language barriers in rural areas.

For Linear Regression model, we achieved prediction accuracy of 75.2% with 50% data usage, and 88.0% with 90% data usage. This suggests that the model may struggle with smaller datasets.

Amir et al.[15] The study conducted at the University of Sargodha in 2019 applied various time series models to historical data (1948-2017) to forecast Pakistan's onion production, finding ARIMA (2,1,2) as the best model, predicting 1854.38 thousand tons by 2030. By applying SARIMA to our dataset, we achieved 73.4% accuracy with 50% data usage

and 87.3% with 90% data usage, which performs worse than Linear Regression.

Yin et al.[16] proposed the LSTM-STL model, combining STL preprocessing and attention-based LSTM to forecast monthly vegetable prices, demonstrating superior proficiency with an Root Mean Square error(RMSE) of 380,and MAPE 7% compared to benchmark models including LSTM, attention LSTM, and STL-LSTM. LSTM on our dataset demonstrates strong performance across all data usage rates, with the highest accuracy of 91.7% with 90% data usage for training. Singla [17] found that wavelet SVR model achieved the highest accuracy in forecasting agricultural commodity prices, particularly excelling in long term predictions. By applying SVR on our dataset, our dataset showed solid performance, with accuracy ranging from 78.1% at 50% data usage to 91.0% at 90%, though it slightly lagged behind the LSTM and Random Forest models. LSTM performed better than SVR and other models in the earlier stages, showing consistent improvement as the training data size increases. It was the second-best model at data usage 90%. Garai et al.[18] Observed that wavelet based combination models, particularly those using the filter with the Random Forest model, generally outer performed other models in predicting onion prices from major Indian markets.

Chaubey et al.[19] This project implements a web based Machine Learning model for predicting real estate trends that forecasts future house prices using multiple algorithms. Ozden [20] collected daily trade volumes and prices of potatoes, onions, and garlic from Turkey(January 1,2018-November 26,2022) to predict 10-day prices using CNN,LSTM and Random Forest, with CNN yielding the best results(MAE:0.047 and RMSE: 0.070).

Samuel et al.[21] Predicted crop prices using data analytics and machine learning techniques, concluding the XGBoost provided the most accurate results. It helps individuals and investors by considering factors, with regression analysis improving accuracy in price predictions.

In our work Random Forest model consistently achieved the highest accuracy across all data usage rate, peaking at 93.7% with 90% training data. SARIMA shows the lowest performance overall.

Table 2: Measures the performance metrics of models.

Data Usage Rate	Algorithms	MAE	MSE	RMSE	R^2
50%	Linear Regression	25.0	625.0	25.0	0.752
	SARIMA	26.6	707.6	26.6	0.734
	LSTM	19.5	380.3	19.5	0.805
	SVR	21.9	479.6	21.9	0.781
	Random Forest	17.0	289.0	17.0	0.830
60%	Linear Regression	21.5	462.2	21.5	0.785
	SARIMA	23.7	561.7	23.7	0.763
	LSTM	17.2	295.8	17.2	0.828
	SVR	19.0	361.0	19.0	0.810
	Random Forest	14.8	219.0	14.8	0.852
70%	Linear Regression	15.4	237.2	15.4	0.846
	SARIMA	16.1	259.2	16.1	0.839
	LSTM	11.0	121.0	11.0	0.890
	SVR	12.5	156.3	12.5	0.875
	Random Forest	9.2	84.6	9.2	0.908
80%	Linear Regression	13.9	193.2	13.9	0.861
	SARIMA	14.6	213.2	14.6	0.854
	LSTM	9.7	94.1	9.7	0.903
	SVR	10.9	118.8	10.9	0.891
	Random Forest	7.7	59.3	7.7	0.923
90%	Linear Regression	12.0	144.0	12.0	0.880
	SARIMA	12.7	161.3	12.7	0.873
	LSTM	8.3	68.9	8.3	0.917
	SVR	9.0	81.0	9.0	0.910
	Random Forest	6.3	39.7	6.3	0.937

Table Summarizes the Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and R^2 values for various algorithms at different data usage rates. These metrics were calculated to evaluate the outcome of Linear Regression, SARIMA,

LSTM, SVR, and Random Forest models to forecast onion prices. Ruekkasaem and Sasananan [22] analyzed 60 months of selling data for Home Pathum Rice and six other crops using various Time Series methods to forecast prices and prediction efficiency was measured by MAPE,MAD, and MSD. Rais et al.[23] Examined the internal integration of major chilli markets in Pakistan between June 2000 and July 2019, finding long run and short run price integration among three markets (Hyderabad, Lahore, Quetta), while Peshawar remained isolated as a result of distance, price fluctuations and seasonal variations. Chen et al. [24] demonstrated that currency and equity market information from commodity-exporting economies can help predict trends, global agriculture prices, as these asset prices reflect future price movements.

Deepa et al.[25] Applied five machine learning regression algorithms to predict cotton prices, the predictions for 2020 were compared with actual prices, and the Boosted Decision Tree model demonstrated the highest accuracy.

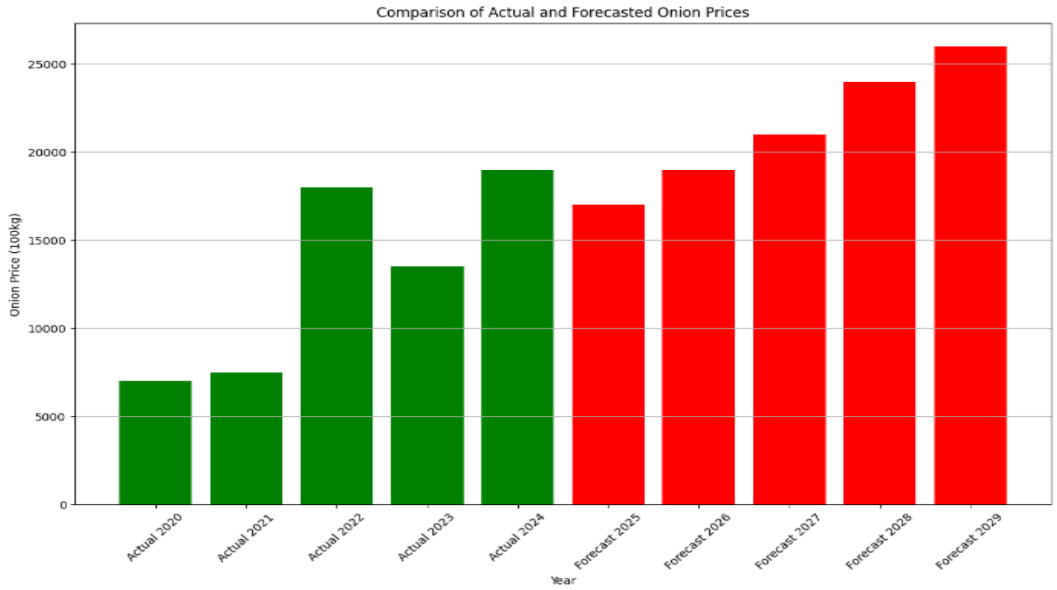

Fig. 4. Analysis of actual versus predicted prices.

Fig 4. Presents a visualization of actual vs predicted onion Prices from 2025 to 2029. For forecasting, we collected a 100kg onion prices dataset from January 2020 to March 2024 and plotted a bar graph. The green bar represented the actual prices of onions from 2020 to 2024. These bars show recorded prices, reflecting fluctuations in the market over those years. Red columns indicated the forecasted prices from 2025 to 2029 based on models, such as Random Forest. The bar chart represents trend evaluation. Green columns indicated a falling and rising pattern, highlighting instability in onion prices from 2020 to 2024.Red column represents the

estimated prices, with progressive trend forecasted from 2025 to 2029 which might indicates that the model forecast substantial price upturn, possibly due to probable dynamics. It assists the easy identification of trends, variations and the model estimated market dynamics for the upcoming years. By examining chart, we can observe the performance of models, anticipate and prepare for future market development in the South Punjab.

5. Conclusion

In our research, we evaluated how well five algorithms performed and which algorithm shows best result. By specific emphasizing, we determined Random Forest (RF) algorithm to be the most effective for predicting onion prices, using RF model we can forecast future onion prices. After though analysis, we identified the best model for predicting onion prices more accurately, which in turn allows us to estimate the corresponding demand and supply. Meanwhile, supply and demand are essential in market stability. This forecasting model can help to stabilize the onion market by preventing imblances.By contrast, the main limitations of our work are the irregular patterns in data and partial dataset accessible.

6. Future Work

In the future, we intend to apply more advanced machine learning algorithms on our dataset. We plan to expand the dataset by incorporating more cities of South Punjab, Pakistan to forecast onion prices through the whole region. Our techniques can also be implemented to forecast the optimal price range of any financial product using associated data set. Furthermore, we aim to use Machine Learning techniques to stable onion production demand, and supply chains of onion, thus, reducing market instability in onion market South Punjab, Pakistan.

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