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Solving Onion Market Instability by Forecasting Onion Price Using Machine Learning Approach

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ABSTRACT

In monetary transactions, the cost is a critical factor. Unexpected cost changes are a sign of market uncertainty. Machine learning now provides massive methods for predicting the expense of products to adapt to demonstrate precariousness. In this study, we look at how artificial intelligence may be used to cope with the onion cost hypothesis. The hypothesis is based on information obtained from a Bangladeshi government entity. We used AI computations such as K-Nearest Neighbor (KNN), Naive Bayes, Decision Tree, Neural Network (NN), and Support Vector Machine to make predictions (SVM). Then we compared and contrasted our techniques to see which method provides the most precise presentation. We see that all of our strategies have a similar execution.Using the approaches outlined above, we attempt to determine whether the cost of onions is optimal (low), efficient (middle), or pricey (high) (high).

1. INTRODUCTION

An extremely fundamental food is Onion in our everyday eating regimen.around more than billion-ton onions are required for 12 months.The unforeseendifference in onion costshas turned into a pivotalworry in the monetary climate of the country. At theend of the year 2019,the country encountered an emotional difference inonion cost. In that yearonion cost was 28 bucks for every kgon the first of January however onthe seventeenth of November it was 228 bucks for every kg.This difference got a major consideration for its strange way of behaving.This cost isn't tolerable to the unprivileged individuals ofBangladesh. Monetary gauging is many-sided due tothe unstable structured nature and vulnerability of information. Other than this thedetermining outcome is affected by climateconditions, efficiency, capacity limit, transportation,and supply-request proportion making anticipating more unpredictable.In this period of man-made brainpower, machines are actinginsightfully.depict machines are utilizedimmeasurably for forecast reasons.For thisreason, we seek to conjecture onion cost by applyingArtificial IntelligenceApproach to our gathered information oncost. Geron showed that for Artificial Intelligence applications assortment of apparatuses isaccessible. Forthe datasetmaking, it is advantageous to use different element determination calculations can be utilized. Making a forecast of onioncost is certainly not a straightforward assignment. We talked about already thecount of variables that affected the expectation. Machinelearning advances us by giving the best forecast strategieslike administered learning calculations, unaided learningcalculations, and support learning calculations. As our workis forecast type we picked administered learning calculation tomake anticipating. This is the primary objectiveof our work.

2. RELATED WORK

Various factors such as the environment, government policies, crop diseases, accessibility, and so on influence the costs of agrarian commodities such as yields, domesticated animals, and dairy. The expenses of these items are unpredictably high and can either be beneficial in the long run or disastrous. The importance of rural business sectors is implied. [15]For a stable economy, ensuring the monetary security of the agrarian inventory network is vital.

Arecanut is a prominent tropical cash crop from India. Prices for areca nuts have fluctuated substantially in recent years, impacting ranchers and suppliers alike. According to FAO data from 2013, India produces the most areca nuts in the world, with Kerala and Karnataka leading the way.in terms of location and creation, Environmental change and governance institutions have influenced harvest creation and costs.

The temperature rise has impeded the production of areca nuts in Meghalaya. In 2011, the high court in India prohibited a segment of areca nut goods, causing prices to plummet. The ranchers were unable to repay the credit or the interest as a result. Ranchers face massive debt, resulting in increased self-destruction rates across the country. Because ranchers constitute the country's major thrust, it's critical to respond to these cost variations.

Understanding the value variances can assist public authorities and associations in making key risk management decisions. The government can provide credit and protection at lower borrowing rates. Ranchers can also make smart decisions when it comes to harvest preparation.

The Kerala floods of 2018 caused havoc on the horticultural sector, particularly areca nut farms, resulting in enormous losses for both the government and farmers. Due to cost differences and diseases, farmers and ranchers in Kerala are switching from areca nut cultivation to different crops. Arecanut output is declining in Kerala, which ranks second in terms of production.

Exams are now being conducted in the financial business areas. Predicting cost changes allows businesses to make critical decisions that ensure financial stability. The value variety is a prominent aspect of the horticulture industry sectors. Predictive analysis using various information mining techniques aids in the identification of cost data patterns and abnormalities. The benefits of information digging in horticulture for crop value predictions are examined, as well as the costs of doing so. Time-series models, such as ARIMA, gullible, remarkable smoothing, and others, were used to predict various types of farmed goods in the public and worldwide business sectors with greater precision.The use of exceptional smoothing, ARIMA, master judgment, econometric model, and cost anticipating in horticulture was discussed. and Composite estimating is used to anticipate pig costs in the United States using conjectures from ARIMA models that respond swiftly to cost fluctuation. Exceptional smoothing, ARIMA, GARCH, a variant of the ARMA model in light of error change, and a crossover ARIMA-GARCH model were used to forecast cocoa bean prices in Malaysia in. The half-and-half model outperformed the exhibition in terms of RMSE, MAPE, MAE, and Theil Statistics. In Punjab, West Bengal, Uttar Pradesh, Andhra Pradesh, Tamil Nadu, and India, the ARIMA model was employed to anticipate paddy prices. ARIMA models were utilized at Hubli, Northern Karnataka, and Kolhapur, Western Maharashtra.The prices were supposed to climb in tandem with the gauge. The Box-Jenkins model was used to estimate coriander seed costs in Rajasthan. In the Assam and Meghalaya business sectors, Box-Jenkins ARIMA models were employed to anticipate the base, most extreme, and midpoint prices of areca nuts. ARIMA (1, 0, 1), ARIMA (1, 1, 1), ARIMA (0, 1, 1), and log ARIMA (0, 1, 1) with a straight pattern and a man-made mediation, and log ARIMA (0, 1, 1) with a direct pattern and a man-made intervention, were the proposed models for the Assam markets.Artificial Neural Networks (ANN), Support Vector Machines (SVM), and Relevance Vector Machines (RVM) are often used to predict non-direct time-series models. SVM is used to forecast stock values in India's business sectors. [16] The expenses of steers, hoards, and grain were forecasted using Multivariate Relevance Vector Machines (MVRVM), an enhancement of RVM.

ANN enables the machine to have a better understanding of the vacillations and deliver more accurate estimates. The Counterfeit Neural Network surpassed the factual techniques of Exponential Smoothing and the ARIMA model in predicting Thailand's rice goods. RNN models were also utilized to anticipate the future of raw petroleum and stock prices. Because the time-series input is sequential and exhibits transitory dependencies, a variation of the Recurrent Neural Network, LSTM, is used.The LSTM model was found to be superior to the ARIMA model in determining retail prices. In Pakistan, the LSTM determination model was used to anticipate wheat production. It's also common to utilize a mix of straight and non-direct models. To anticipate hoard and canola costs in Germany, a combination of ARIMA and Elmann brain network (ENN) was utilized. Based on assessment outcomes, AI models were determined to be more traceable than factual strategies.

3. PROPOSED WORK

Our work philosophy includes data collection, information investigation, computation execution, and evaluation.

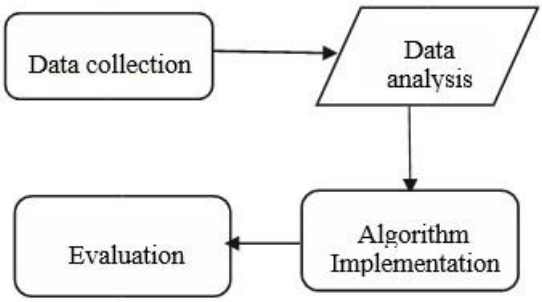


Fig. 1.

The system is depicted in this diagram. By following the procedures, we were able to achieve our perfect result.

A. Data collection:

We got the information we needed from the Agriculture website. Then, every day, 730 cost examples were gathered. This data is unstructured, mathematical, and time-series in nature. We followed the steps below to begin chipping away at this information.

B. Data Analysis:

To perform calculations, we structured our data into a design. As boundaries, I considered the year, month, date, season, area, cost, and classification, which is a gotten trait apart from cost. The information in our acquired dataset was not in perfect condition because it was mixed up with unwanted data. Before doing the calculation, we needed to remove any unnecessary data from the dataset. As a result, we used the well-known Machine Learning tool to filter out irrelevant data to create the desired information outline.

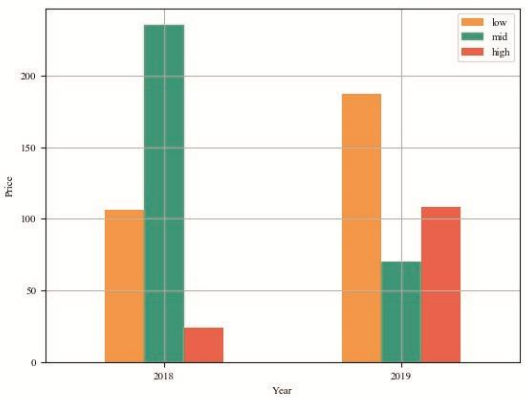


Fig. 2.

We plotted the year on the x-pivot and the cost on the y-hub to represent the onion cost for two years, 2018 and 2019. After classifying the costs into these three categories, we plotted them into the diagram as low, mid, and high. The orange bar represents a low cost, the green bar represents middle cost, and the red bar represents a high cost. We can easily determine how long the cost was low, mid, or high based on the figure.

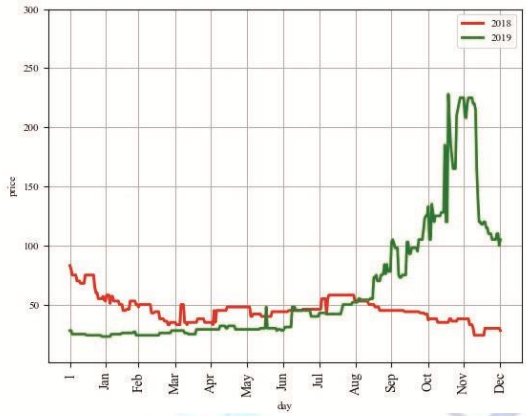


Fig.3.

This diagram depicts a line graph with the month on the x-axis and cost comparisons on the y-axis. Outwardly, cost vacillation is depicted in Figure 3. We gained knowledge from the facts in this chart through information examination. We saw that when onion prices were high at the beginning of the year, they would drop by the end of the year. The cost of onion was low at the beginning of the next year, and we predicted that it would be high by the end of this year. We saw that previous years had followed this pattern as well. Taking into consideration this architecture, we needed a year code as an additional barrier to help us predict onion costs more precisely.

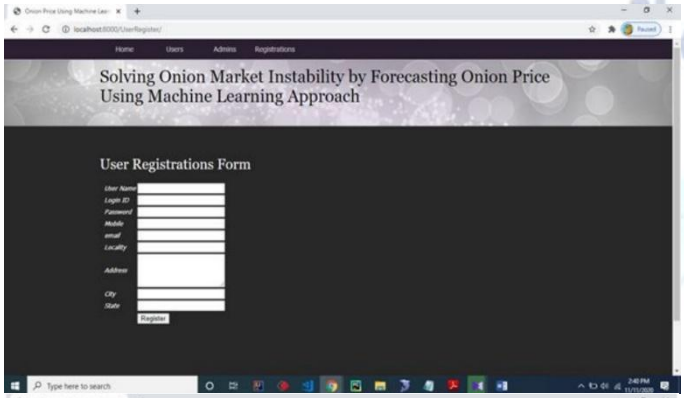
C. Algorithm implementation: To begin, we divided the onion cost into three classes and then used administered learning calculation methods, specifically order calculations. After completing the data analysis, we now have a dataset that is ready for calculation. In this piece, we applied each computation one at a time and saw the effects. Chevalier, Then we discovered the exact rate at which these calculations were performed. For the forecast of onion cost, we used several AI calculations. KNN, Nave Bayes, Decision Tree, SVM, and Neural Network are examples of these calculations.

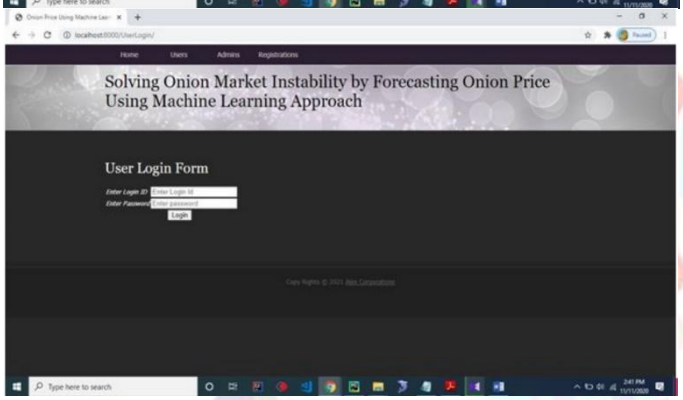
D. Evaluation:

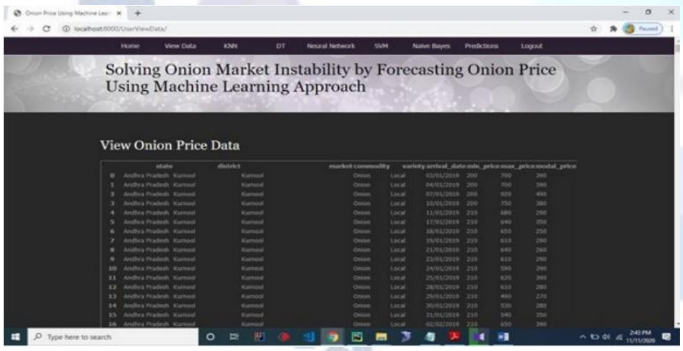
To begin, we organized a dataset and then ran five distinct machine learning calculations. Each calculation produced was almost certain to predict outcomes. We

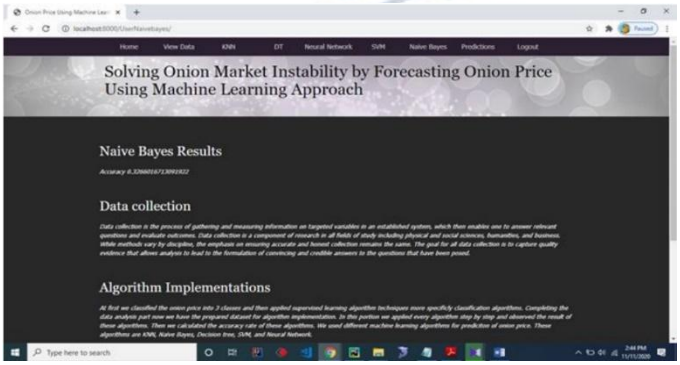
will chip away at the outcome for additional perspective by unparalleled this interaction in the trial result area.

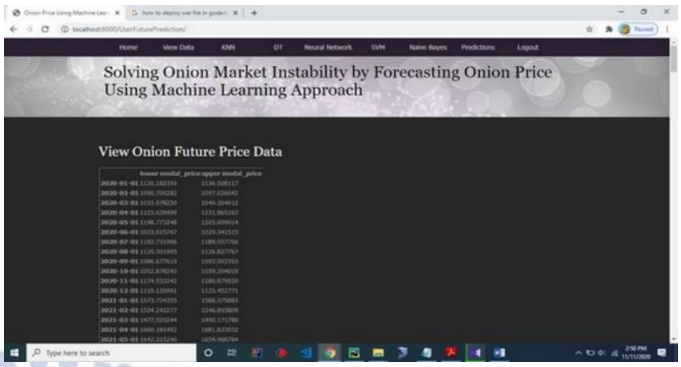
4. RESULTS











5. CONCLUSION

In our research, every calculation we did intently. We explored a total of five calculations execution and observed the best calculation at a superior onion cost forecast.

At long last, gauge the cost of onion in the future. Contingent upon this gauging value we can ascertain the interest and distribution of onion, as we probably are aware interest supply assumes the fundamental part in a market harmony state.

Presently on the off chance that to compute the future interest onion supply in light of this expectation,from this, we can keep up with the balanced state ofthe marketand assist us with eliminating onion market precariousness. The primary constraint is the strange way of behaving information.

Conflict of interest statement

Authors declare that they do not have any conflict of interest.

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