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Research Article

An integrative approach to agricultural challenges: Predictive modeling, crop alternatives and automation

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ABSTRACT

The present research will explore the possibility of an integrated method of enhancing agricultural practices in India that utilize machine learning, data science, and Internet of things (IoT) applications. This explorative research is a method of addressing the gap between traditional and modern farming technologies by integrating IoT and data science technologies and supplying the farmers with real-time monitoring and actionable insight and direction through data-driven decision-making. The study is separated into three sections that include predictive modeling, evaluation of business value, and Internet of things (IoT) implementation. This is the main finding of the study that helps develop a predictive model with up to 99% accuracy and make individual recommendations on crop choice and fertilizing in accordance with the soil qualities and environmental situation. Also, the Arduino-based system to an NPK sensor enables the real time checking of soil nutrients to optimize fertility of the soil and agricultural management. The results show that the possibilities of better harvest, fewer losses, and maximized returns can be achieved by using these technologies. The up-to-date interface created in the context of this study allows agriculture producers to make valid decisions and balances between tradition and innovation in the context of sustainable and resilient farming in India.

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INTRODUCTION

Healthy agriculture is the backbone of the Indian economy; it is the occupation of about half the population in the country, meaning it is quite important Its healthy states are mostly dependent on the state of the Indian soil, directly impacting the yield and quality of the crops The better the soil, the better the agriculture Reserve phytophthora control Mycotoxin solutions [1].

Nevertheless, even though it is crucial, the Indian farmers have numerous problems which impede them on the way to the enhancement of crop quality and sustainable agriculture. These stresses are posed through the varied weather, land degradation, fluctuating market prices and lack of access to information and resources [2].

Agricultural practices can be rooted in pre-historic concepts shared over thousands of years and may not keep abreast with current field or transformation of agriculture. Confidence on anecdotal data and hearsay also exposes farmers to incompetence and stumbling block in making sound judgments and productive in the farming industry. [3] The conventional practices that dominate agriculture today tend to yield negative results implying that innovativeness is necessary. In order to increase agricultural output, new applications and integration with the recent technologies have become the subject of attention. Unforeseeable rain patterns as a result of climate change is a motivating factor in the promotion of precision agriculture [4, 5].

There is need to take another step further in exploring this joint effort so as to appreciate the urgency of the challenges affecting the agriculture. Considering it is projected that the global population will reach over 9 billion people by 2050, the premises facing the world food supply are explicit. Traditional processes are in an unprecedented position facing a situation of limited resources and climate change. In this context, it is the incorporation of prediction models, variable farming as well as technology that brings forth some hope as it signifies a radical change in the sector of agriculture [6].

In order to guarantee the use of permaculture, the following technologies ought to be applied to include blockchain, the internet of things (IoT), big data, and machine learning (ML) [7, 8]. Amongst them, it will help to teach about agriculture which is the best approach to the problems present and in the future. If this big data on agriculture could be created and utilized in making decision in the agricultural sector, then most of the world food problems would be solved. As an example, when farmers have possibilities to develop information or maps about certain environmental conditions around their farms, they can apply such technologies as smart farming, farming, and vertical farming. Big data in the field of agriculture has been found to enhance yields, decrease expenses and enhance sustainability [9, 10]. In the focus of this paper lies collaborative approaches to allow the combination of learning technologies, data science and the Internet of Things (IoT) to implement solutions to challenges of the Indian agriculture. It is better understood through the main aim of transforming traditional agriculture through empowerment of the farmers with insight and predictive analytics at three levels. In the first step, it is all about predictive modeling, which employs advanced mathematical algorithms to propose crops and fertilizers in consideration of other intricate conditions like the soil and climate conditions [11].

Data mining came to play full role in crop decision-making during the course of growth; it guided in choosing appropriate crops to use in certain applications as well as technical hitches. Complex neural networks are among the intelligent methods that have been appealing in developing agriculture as a whole. This paper will outline the history of artificial intelligence and show how it can make negative data meaningful and forecast the crop size based on the past market data records [12, 13].

What is more important is the fact that such a collaboration gives not only practical solutions but also proposes the shift towards the more efficient and effective agricultural sector where the role of technology is crucial in future agriculture development of India [14, 15].

The following part of this article describes the design, process, and findings of the study, and crop forecasting solutions, as a subcategory of soil fertility and crop friendlier search and monitoring.

The third and the last step involves integrating Internet of Things (IoT) through the development of novel Internet of Things (IoT) devices that can be used to extract the vital data in a short time period. The device comprises NPK sensor, an-arduino Uno R4, and an OLED display that allows the process of transmitting data to the web to be analysed. The web site employs the capabilities of serial communication and Wi-Fi to execute on the predictive models developed in the initial step to deliver direct and on-time information to farmers in the fields [16, 17].

Along with this, a convenient web site was developed on Django framework to make it reachable and usable to the farmers as well. The site is a syndicating model that combines all three levels of the research, where farmers can benefit in an intuitive manner access to forecast models, market price forecasters, and topical information about the activities in real-time Internet of Things (IoT) inspection [18].

It is hoped that with the technology of machine learning, data science, Internet of Things (IoT) web application development, the knowledge and toolset that is used by Indian farmers to deal with the nuances of modern agriculture will be provided. The goal of the program is to enhance the agricultural performance stability, and the improvement of the health of the rural population by boosting leadership through personalized recommendation, predictive information, and real-time monitoring available on the web page [19].

Machine learning To automate agricultural processes using machine learning To find a universal solution to key agrarian problems by developing a predictive model that will help optimise the nutritional structure and identify crops based on soil type [20].

The study seeks to maximize yield using the predictive modeling, suggest alternative crop choices, automate the farming process with the incorporation of the Internet of Things (IoT) and offer data-driven decision making to crop producers to improve sustainability and the profitability of the farm [21]. These goals form the core foundations of this study project, which regards a comprehensive exercise that would aim to maximize agricultural activities, foster sustainability and establish modern technological paradigms in the farming sector [22].

Smart Agriculture Overview

Agriculture has undergone numerous revolutions that have helped the industry to become lucrative and profitable. Domestication of the ancient species of plants (10,000 BC) had given birth to the first organization and civilization in the world. Agricultural mechanization (1900-1930) brought about machines and mechanization farming methods that helped in making work more efficient and made farmers more prolific [23]. The Green Revolution (approximately 1960s) provided farmers with the new crops and agricultural chemicals. Internet of Things (IoT) technology made it possible to develop plants with pre-selected features, including higher yields and resistance to insects, drought, and herbicides, in the late and early centuries (1990 to 2005). Digital transformation has been able to make people sustain and prosper in the long run [24]. Initial stages of digital transformation are concerned with automation technology involving some computerized tasks [25].

The historical context of the way agriculture has been developed over time along with technological achievements offers a manifestation of time of the farmers. Incorporation of ancient skills and technologies, e.g., machine learning, is crucial to sustainable and successful farming [26, 27].

History and development of farming; It depicts the critical moments when one should consider making adjustments due to the changes in technology, global warming, customer preference and international guidelines. The historical background points to the issues currently met by agriculture, in terms of initial agriculture to technical changes in the Industrial Revolution and the industrial age of the 20th century [28, 29]. Commercial technology pioneered precision agriculture, which is based on the analysis of data, the use of sensors and satellites and informs the attempts of farmers to better use resources and limit negative impact on the environment. The justification circles around the significant role of the AI in the agricultural sector because it is sensitive to the size of datasets, algorithm parameters, and terrain type and purpose prediction. Deep neural networks are a valuable component in artificial intelligence and are credited with the help they provide fertility prediction, crop strategy and land management particularly organic fields. Conclusively, the move towards advanced agriculture is not only significant to be considered as a practical move but a major step towards ensuring the safety and efficiency towards the full-fledged cyclic agricultural activity [30, 31].

MATERIALS AND METHODS

Predictive Modeling

Model development

High performance predictive model was developed via the use of ensemble learning concepts like bagging to ensure recommendations on the type of products to apply alongside fertiliser applications based on soil properties and environmental conditions affecting the region.

The datasets used to develop both predictive models and market price predictions in dented this research constituted of series of data collected on different government agricultural websites. Particularly, information was gathered through Directorate of marketing & inspection (DMI) website (agmarknet.gov.in), India council of agricultural research (icar.org.in) and the ministry of agriculture and farmers welfare (agricoop.nic.in). Data was retrieved in areas like Kolhapur, Solapur, Satara, Sangli and Pune over the past 10 years between 2012 and 2022. The data consist of a set of about 37458 samples comprising of about 1 GB of soil characteristics and crop yield data, content of different variables concerning the tables, with region name, soil color, nitrogen content, phosphorus content, potassium content, pH value, rainfall amount, temperature, crop type, and crop yield being some of them. Also, about 500 MB of market price data were collected, 17467 samples relating to the historical prices of the major crops over the past 10 years (2010-2020). This data comprises such variables as the name of a region, a market, a product, a variety, a classification, a floor price, a ceiling price, a mode price, and a date.

In order to carry out an analysis, the following pre-processing methods have been used. To ensure the attributability of data incompleteness, missing values were imputed, and to ensure trait measures were scaled on a consistent basis, standardization was done. Nominal variables, e.g. field location, crop type and fertilizer type, were coded into numbers. This data was then separated into train (70%), and test (30%) in order to adequately assess model performance. Several algorithms were tested, such as, logistic regression, decision trees, random forests, gradient boosting, AdaBoost, SVM, K-nearest neighbors, naive Bayes, and multilayer perceptron with bagging model returning the highest accuracy, reaching 99 percent.

Preliminary data

This significant phase is the preparation of the data set to be analyzed with attention. The imputation of missing values, standardization of trait scales, coding of categorical variables are the methods used. The categorical behavior, that is the names of regions, browns, crops, and fertilizers are quantified into numbers referring to relationships through the machine learning algorithms [32, 33].

Coding of categorical variables

Catergory variables like field location, crop type and type of fertilizer used were coded into numeric values that would be used within the predictive models. This has to be done through the creation of a dictionary whereby certain categorical based items are assigned analogue indices. The result encoding mode can be used to good effect to merge the distributed information into further machine leaning models.

Specification of input and output variables

The model has a couple of input variables whose requirements include the name of the region, color of the soil, nitrogen, phosphorus, potassium, a crop, pH, rain, and temperature. The forecast targets crop yield as variable of interest.

Model selection

The SVM, RF, NN, Naive Bayes, decision tree, bagging and boost machine are used to enhance the accuracy and power of forecasting [34].

Model evaluation

Known material libraries of classified models in the well-known Sci Learning are dedicated to analysis. The data is categorically split into training (70 percent of the information) and the testing (the remaining 30 percent) data sets. This categorization approach enables one to obtain general information on modeling data that he/she has never encountered before.

Training data

Data on agricultural history of such regions as Kolhapur, Solapur, Satara, Sangli, and Pune are used to predict the education, and support various soils, weather conditions and crop preferences.

Input parameters

Entries on domain name, brown, nitrogen, phosphorus, potassium, pH, rainfall, and temperature, and other available options based on the products are accepted as input.

Model selection

The performance of different models can be compared in choosing before taking into consideration the evaluation. Models run available include logistic regression, decision trees, random forests, gradient boosting, AdaBoost, bagging, SVM, K-nearest neighbors, naive Bayes and multilayer perceptron. Subsequently, the Bagging model proved to be the most optimal one with the accuracy rate of up to 99%.

Model output

Once the parameters have been Keyed in, the model makes farmers specifically recommendable crop and fertilizer choices.

Recommendations

Where there is no crop presently growing on the land then the model would indicates that the crop is optimal and would involve regimes of fertilizing the soil in order to yield more. Where there are crops already established, application of suitable fertilizers with the aim of supplementing nutrients that exist and enhancing crop health and yields is advised. Other farms and fertilisers are also recommended to ensure farmers have choices and variety hence cutting on risks taken [35].

Implementation and impact

This is built into an easy to use interface that enables the farmers to use through the web or mobile platform.

User interface

Farmers are capable of making crop selection and fertilizing decisions that are suitable to their types of soil and environment. The aim of developing the forecasting model was to increase agricultural production levels, resource effectiveness and sustainable agriculture among farmers.

Strengths

The modeling phase is personalized and based upon the insights gleaned out of data and therefore the farmer is able to beat the status quo and get optimal out of his/her efforts which ultimately helps in the economic growth of the villages.

Market Price Prediction

Model development

In this step, the value of major crops will be estimated in the target by Long Short Term Memory (LSTM) network to estimate time series analysis. Apply pre-processing analysis such as anomaly detection, optimization to clean the dataset before training it to maintain quality and consistency in it.

Completely reliable information:

This information was received by dint of agricultural websites run by various governments.

Pre-processing Technology

Advanced detection

Employ statistical methods or the use of machine learning algorithms to determine and solve issues with products. Replicate the information This will assist in minimizing the influence of reported data on the performance of the model and raise the reliability of the forecast in general**.**

Normalization

Transform the data into normalized scale to measure characteristics to a new value (normally zero to one). Normalizing all the input parameters into the training model plays the part of equality in contributing to the training process and favorable convergence during optimization.

Model selection

LSTM neural networks have been selected because they are able to take capture a long span of the data series thus more suited to the task.

Training data

Sangli and Pune have a history of trade in crops such as Jowar, Gram, Ginger, fruit, maize and rice of the past decade.

Input parameters

This Model is Region Name, Market Name, Product, Variety, Class, Min Price(Rupee), Max Price (Rupee), Modal Price(Rupee) and Date Price.

Model output

The LSTM model is developed such that it would provide forecasts (quarterly) of the minimum, maximum, and crop prices of the target region.

Predictive insights

Because farmers know the market in great detail, they can anticipate fluctuations in the market and change farming practices, farming and sales strategy accordingly. In price forecasting, quarterly forecasting increases the crop profit-making of the farmer through optimum crop selection and harvest and market accessibility and eliminates costly financial risk of price fluctuations.

Implementation and impact

The development of the intuitive web applications is achieved based on Django framework Existing storage bags and LSTM models are built with the framework of the Django framework. The web has the capacity to predict design which is facilitated through this integration.

Web Platform Integration

Facilitate the provision of farmers with estimates of the market price on the Django web site within the easy to use interface to offer validity and validity. By becoming a part of a centralized system, farmers will be able to incorporate market intelligence in their decision-making process maximizing profits making it smarter, and more profitable, farming. The packaging mode employed in the system is using a machine learning mechanism that contends with various information such as soil quality, climate and crop patterns as examples. The analysis of this model can offer the choice of the best crop to the farmer of a certain agricultural context through the availability of satisfactory and timely market price predictions that enable informed choice of crops and that also enable farmers to make better choices about business opportunities and their involvement thus resulting in greater profits and livelihoods. This adoption of market price forecasting shows that the company is interested in ensuring that its farming community is empowered by giving them the resources they require to make and maintain a good business in agriculture in India.

Internet of Things (IoT) Integration

Device design and components

Nowadays, the Internet of Things (IoT) devices is designed and manufactured in such a way that any information could be gathered within the ground in a short period of time and then be transferred to a location where it could be analyzed. The device consists of numerous parts each playing a certain role in gathering and transferring of information.

NPK sensor

NPK sensor is also fitted into this device to enable it to know the nitrogen, phosphorus, and potassium that is found in the soil. The NPK sensor deployed in this system is specially made to be very sensitive to the amount of nitrogen, phosphorus and potassium in soil. It measures 0- 2000 mg/kg per nutrient with precision of 1 mg/kg - accuracy of 5 mg/kg. The sensor has a temperature range between 0-50 o C and conveys the information through a DC value with regards to the concentration of the nutrients in the form of an analog voltage signal. It is fed by a 5V DC and connected easily with Arduino analog input. NPK data is transferred to a database through a serial interface with data properly formatted and compiled. The machine learning data has features intact around the levels of NPK, soil moisture and temperature had 1000 samples taken in various soil types. This data is subject to preprocessing to address noise and missing values in order to use it as a proxy in training machine learning models. Findings are illustrated in graphs and tabular forms which are clear and would present evidence on how different NPK measurements influence soil health and plant growth with the help of legends as well as annotations. All technical specifications of the system are recorded, Arduino installation, sensor calibration, etc.; reference to literatures guarantees reliability and precision of the methodology used.

RS485 TTL converter

This TTL converter is included to ensure that there is a link between the NPK sensor and the microcontroller (Arduino Uno R4). This converter enables transmission of sensor data in the RS485 format so that it can be used with Arduino boards.

Arduino uno R4

Arduino Uno R4 micro-controller would serve as a central stand-in processor to IoT devices. It obtains information coming in NPK sensors through TTL transformers and begins transporting it on the central platform. Data collection, operation and communication occurs with the aid of programmed Arduino boards.

OLED screen

The OLED screen module is incorporated into the device in order to have instantaneous display on location information. The screen saves farmers the stress of accessing the soil through a third party and making crucial decisions about a location as well as being able make immediate interventions when need be.

Data Transmission and Analysis

After the dynamics of locations is comprehensively gathered by Internet of Things (IoT) devices, it is transmitted to the central office where it will be analyzed in more detail. Redirect the processes of data transfer via the usage of the serial communication and Wi-Fi capabilities of the Arduino Uno R4 microcontroller.

Serial communication

The Ardino board plays a role of transferring the data to the central processing unit and this is done through connection. This communication procedure is required in case the data collected by the Internet of Things (IoT) devices is securely and efficiently sent to the platform.

Wi-Fi connection

Along with the communicational connection, there is also the Wi-Fi connection to Arduino Uno R4 through the use of the ESP32 module. This enables data to be transferred wirelessly into the central platform giving flexibility and convenience of data transfer.

Centralized platform

Information, which is sent down the ground is received and processed by the central system, which was developed using the Django framework. The platform contains a web access interface in which the data analysis and visualization tools could be employed. The framework of Django permits smooth integration of the information on different sources and enables farmers to receive immediate overview.

Implementation and impact

Application of Internet of Things (IoT) technology in agriculture has a number of advantages such as the possibility to gain an insight into the specifics of soil in real-time, prevent excessive nutrient content, and make decisions based on the analysis of the data.

Real-time monitoring

Internet of Things (IoT) devices track information about soil in real-time to allow farmers to evaluate the condition of the soil and change the way they fertilise it in time.

Proactive management

With the IoT devices, there is instant response to availability of food giving the farmers the chance to address food shortage and fertilizer consumption enhancing growth and production standards.

Data-driven decision making

This is because of the central platform as it assists in the management of data analysis and insights, thus farmers make real time decisions based on the information delivered through food. With the aid of the internet of things (IoT) technology, farmers can integrate real-time farming in their process to make those farming activities much more efficient and sustainable.

Circuit Diagram and Block Diagram

Figure 1 shows circuit diagram of the predictive model system performed during the research. This diagram gives a more in-depth visual breakdown of the parts and connections necessary in the implementing the predictive model. Its major elements are sensors that determine the content of soil nutrients, an Arduino microcontroller to process data and data communication interfaces to transfer information. The circuit also combines several aspects to make sure that

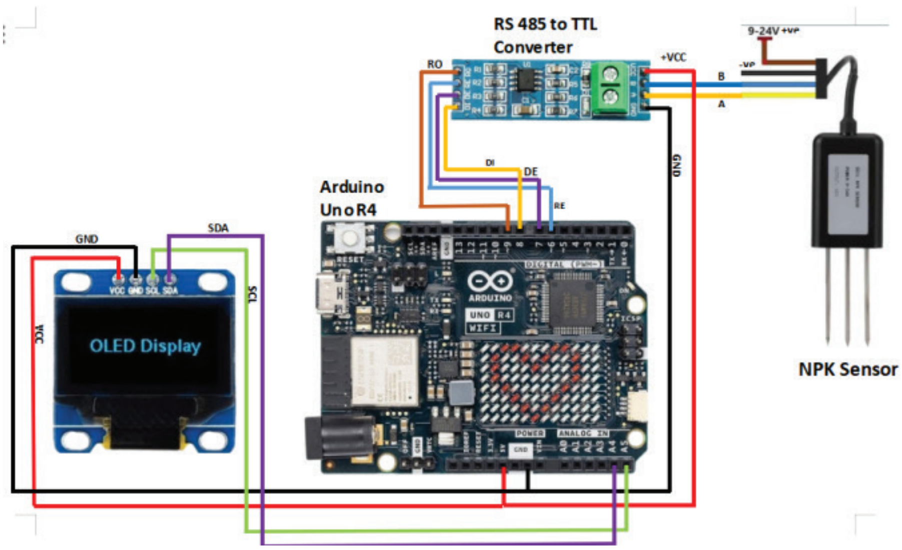

Figure 1. Circuit diagram of predictive model.

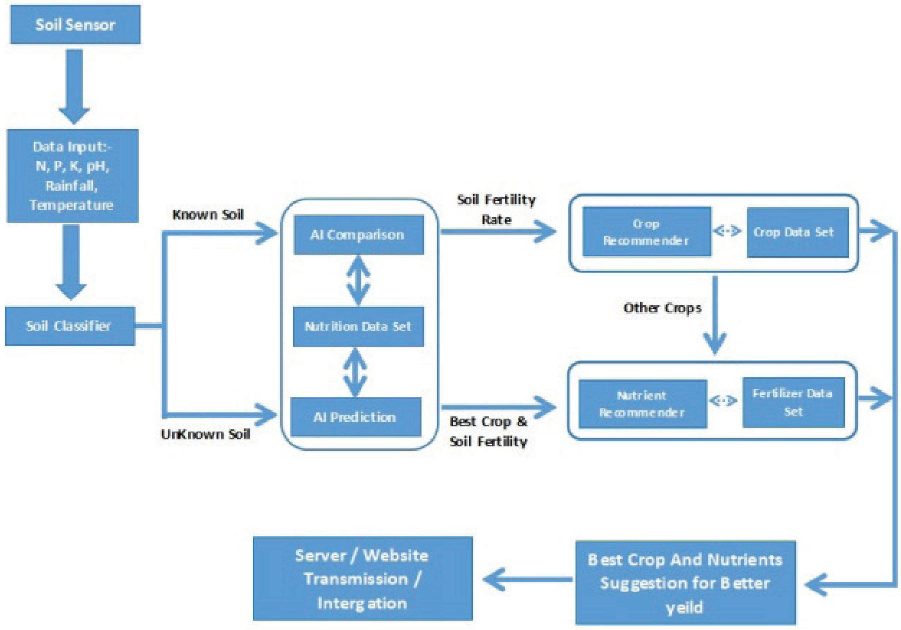

Figure 2. Block diagram of predictive model.

actual dataS in the field is precisely presented, processed and changed to centralization platform. Such an arrangement is the core of the predictive model that allows to make accurate crop and fertilizer recommendations characterizing soil conditions.

Figure 2 shows the block diagram of the proposed predictive model with its data flow direction and the connecting of all the modules. The diagram indicates the mechanism behind this step which includes data acquisition using the sensors to the data processing on the Arduino microcontroller to the analysis of data using the machine learning algorithms. The block diagram also indicates how the hardware items and the software systems interact, and the chain of events that produces some insights that make predictions. This decoupled design—in that it is modular in nature and scaleable and flexible to incorporate new sensors and analytical capabilities to improve upon the models accuracy and functionality--will enable us to add more data points and increased accuracy and usefulness to the model.

Figure 3. Block diagram of predictive model.

Figure 3 shows the predictive system model that has been developed. This prototype is able to consolidate all the hardware components such as sensors, microcontrollers and communication modules in a consistent and useful framework. The prototype is a kind of model of the theoretical model which can be tested and validated in practice by the parameters of the system. It demonstrates implementation of the circuit and block diagrams in real life application confirming that the model can be practically used on the field to gather and analyse information in order to give crop and fertilizer recommendations.

RESULTS AND DISCUSSION

Predictive Modeling Results

With the predictive modeling process, encouraging results were achieved that offered recommendations on crop choices and fertilizer use by offering a 99% accurate forecast on environmental and soil conditions. Overall, the classification model scored accuracy of 99% on the testing dataset, which shows that it works effectively to make proper recommendations on the type of crops and fertilizers that farmers should grow.

Figure 4. Sample testing done on prototype.

The model is easy to read and displays appropriate crops and fertilizers according to such input as the name, terrain, rainfall, and temperature. The farmers mentioned that they were highly satisfied with the presented recommendations and were in agreement that it was environmental friendly and went along with local farming.

The illustration Figure 4 is the sample testing performed with the prototype model. This image illustrates the functioning of the prototype showing its capabilities to collect the soil data and process information with the help of the integrated system. The testing stage is significant to prove testing the accuracy and reliability of predictive model. It entails a comparison of the carbon footprints in the prototype to the actual field and crop performance, which further make the system more useful and able to give farmers with an actionable and reliable information. The prototype testing provides the demonstration of the practical applicability and the efficacy in the agricultural working environment.

Impact on agriculture

The farmers who put into practice the recommendations of the model experience growing yields, less fertilizing and they become more efficient. The predictive model assists in adopting permaculture practices and to ensure economic improvement of farmers by proposing recommendations pertaining to particular farming areas.

Table 1 discusses the difference between accuracy, precision, and recall of the use of various machine learning models, including logistic regression, decision tree, random forest, and gradient boosting. Gradient Boosting and Random Forest have the best accuracy and hence can make the best recommendations on crops and fertilizers to be used to increase agricultural productivity and sustainability.

Table 1. Model compatibility result

	Logistic regression	Decision tree	Random forest	Gradient boosting
Accuracy precision recall	0.615953	0.992614	0.999261	0.998523
	0.410916	0.97885	0.997596	0.996422
	0.449497	0.992472	0.998922	0.996422

Table 2. Model compatibility results

	AdaBoost	Bagging	SVM	K-Nearest Neighbor
Accuracy precision recall	0.463811	0.996307	0.593058	0.937962
	0.264857	0.996814	0.351363	0.897532
	0.280842	0.99317	0.299619	0.888587

Table 3. Model compatibility results

	Naive bayes	Multilayer perceptron	XGBoost	CatBoost
Accuracy precision recall	0.655096	0.815362	1	0.994092
	0.549116	0.68206	1	0.993303
	0.632563	0.663501	1	0.986283

Table 2 compares the additional machine learning models by its accuracy, precision and recall: AdaBoost, Bagging, SVM and K-Nearest Neighbor. Bagging has the best performance reports implying that it is powerful in delivering the right crop and fertilizer prescription to support agriculture and sustainability in practice.

Table 3 also compares accuracy, precision, and recall of such models as the Naive Bayes, Multilayer Perceptron, XGBoost, and CatBoost. The excellent results in accuracy and recall here demonstrated by XGBoost and CatBoost demonstrate that techniques are efficient in predicting crop yields and making agricultural decisions to improve productivity.

The regression line in Figure 5 is the difference between the actual and the predictive result generated by machine learning model. Here the line gives the figure of how much the model is accurate in predicting the actual observation and the difference between the best line and the actual observation is the deviation. The regression line can help provide information on the bias and variability of the prediction model along with the distribution of the data points around the regression line may provide information regarding the accuracy of the consistent nature of the model. Regressions analysis can enable those who are conducting research to assess the overall effectiveness of machine learning models and define where the accuracy can be increased in the prediction.

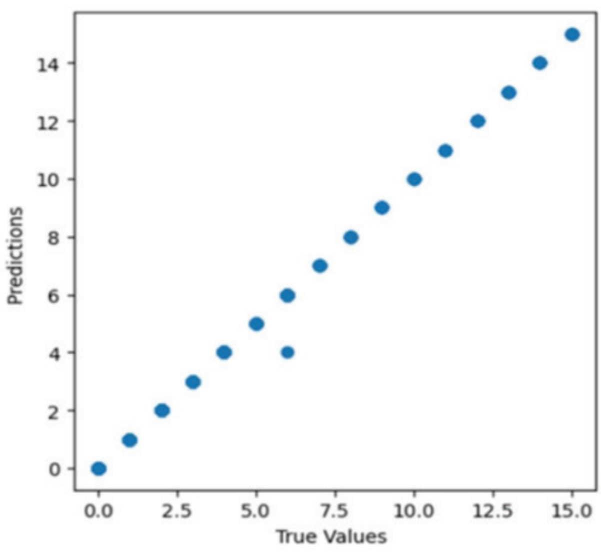

Figure 5. Actual vs. predicted values.

Market Price Prediction Results

The price forecast level that is market price forecast would enable the farmers to make decisions and decisions on crops, and marketing decisions based on an understanding of the differences in prices of major crops in the target region. The LSTM model reported reasonable outcomes in predicting the price of the quarter with an accuracy of 70% -75 % of all crops.

Price forecast accuracy

Perfectly contrasting the seasonal variation and the long-term market trends on the prices, the LSTM model offers a rationale to the farmers with regard to the minimum-upper-end and price range. It is recommended that farmers should utilize these forecasts to make better crop choice, timing of sales, and market engagement and thus augment their profitability and shield them the financial risk.

Value for farmers

Access to the right market prices helps farmers to negotiate better prices, long-term planning of production cycles and diversity of crops to meet the needs of the economy. By linking agriculture with the vibrant market, farmers answered this by increasing the level of the farm price prediction and improve the convenience and the competitiveness of farmers in business.

Figure 6 indicates the learning curve of the long short-term memory (LSTM) framework on the training process of predicting ginger prices. The curve shows the performance of the model in each successive epoch indicating the reduction in both training and validation loss. Convergent, well-behaved learning curves show that the model is learning well and there is good generalization highlighting the fact that the validation loss follows the training loss.

Figure 7 depicts the LSTM learning curve of gram: this is the model training, validation performance measured over different epochs. It demonstrates the incidence of the model loss under the impact of the training in the data, to minimize the variance of the predicted and actual values. The curve aids in determining whether the model is over-fitting, under-fitting or doing their best the curve can also aid in determining the model that is applicable in solving a certain task.

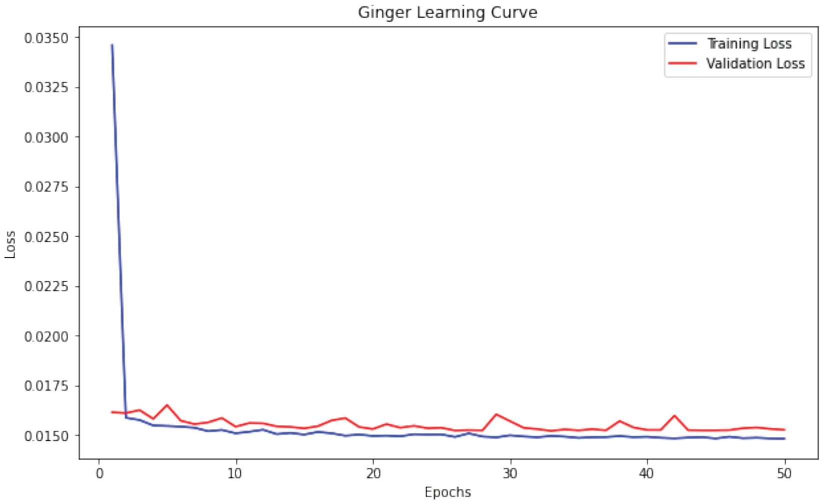

Figure 6. LSTM learning curve for ginger.

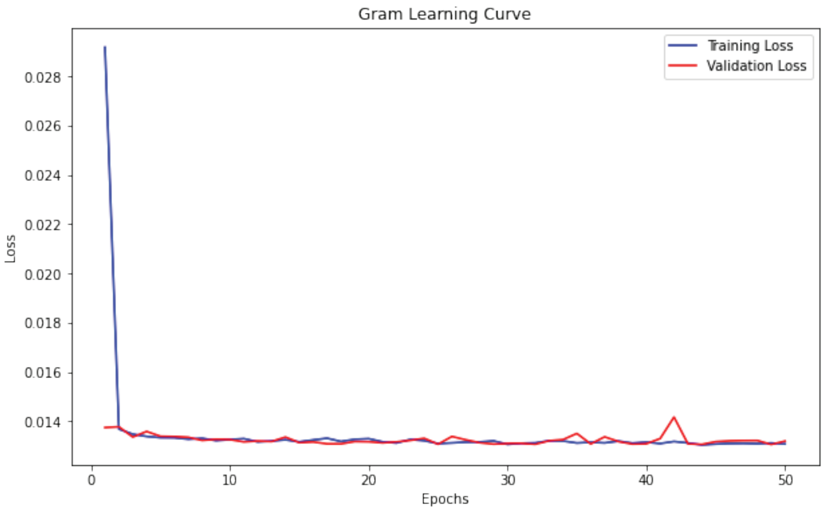

Figure 7. LSTM learning curve gram.

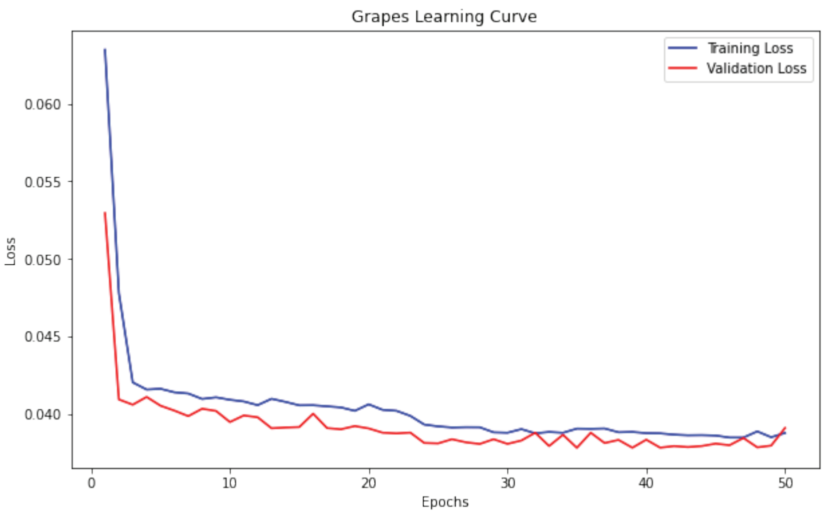

Figure 8. LSTM learning curve for grapes.

Figure 8 shows the loss values exhibit an LSTM learning curve during the training and validation of grapes. The consistent down turn in the values of losses indicates the growing precision by the model in forecasting the grape prices. The said curve gives an insight into the efficiency of the learning during the model and is used to refine the model to attain enhanced predictive capabilities.

The learning curve on maize depicts the improvement in the error at successive stages of training of the LSTM model in Figure 9. This figure plays an important role in assessing how far the given price trends of maize are reflected by the model. The closeness of the training and validation curve signifies that this model will be well suited to making predictions on new data and the effectiveness of this model in price forecasting.

Figure 10 illustrates the LSTM learning curve on Jowar to show the progression of loss by the model throughout training. The learning graph will be instrumental in determining the effectiveness of the model as well as the appropriate number of epochs in order to avoid overfitting. The tradeoff in training and validation loss is also satisfactory showing that a stable predictive model was compiled.

Figure 11 LSTM learning curve of wheat demonstrates the training and validation losses across the epochs that illustrate how the model learns. This value is critical to determine that the model is forming the regularities in the wheat price data. An aligned curve that shows that the values of loss fall is employed to indicate an effective training process with the possibility of the correct prediction of prices.

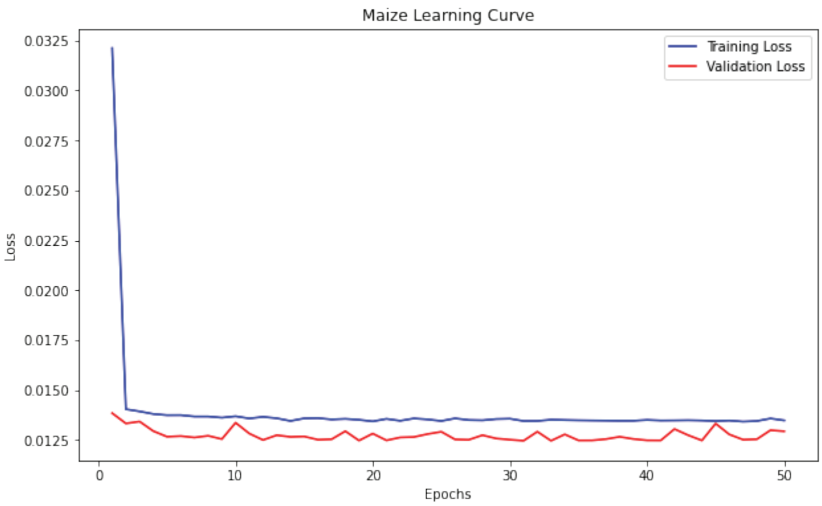

Figure 9. LSTM learning curve for maize.

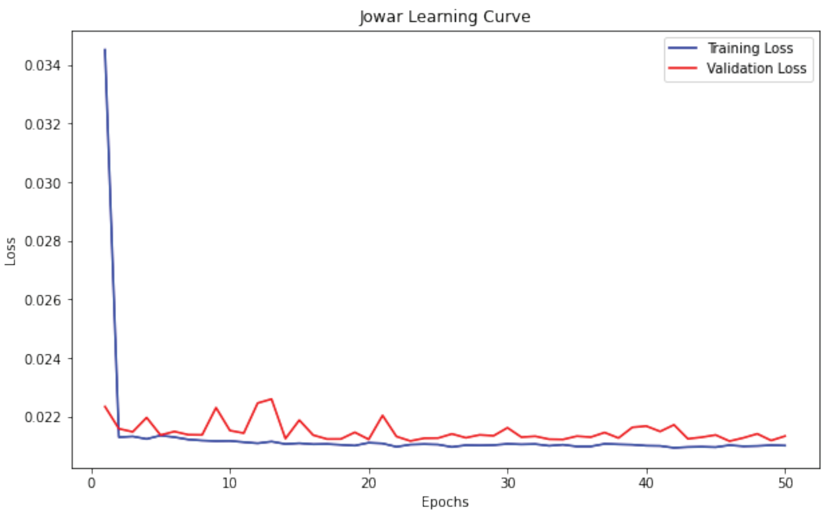

Figure 10. LSTM learning curve for Jowar.

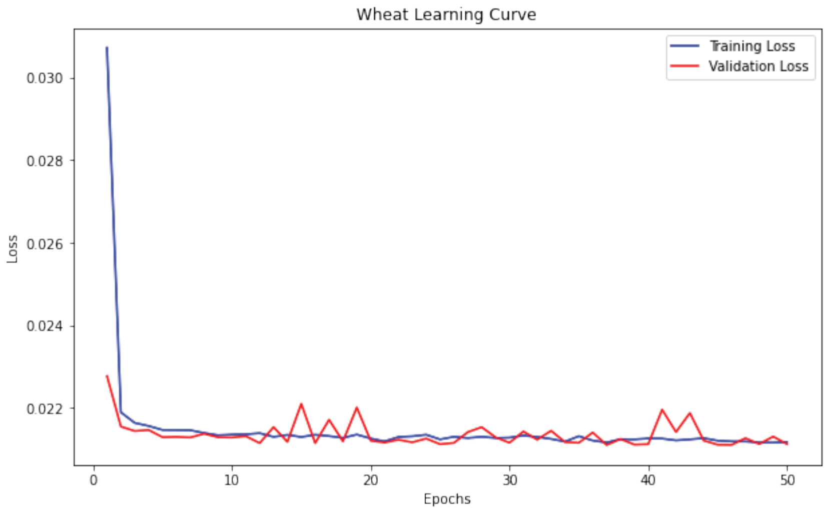

Figure 11. LSTM learning curve for wheat.

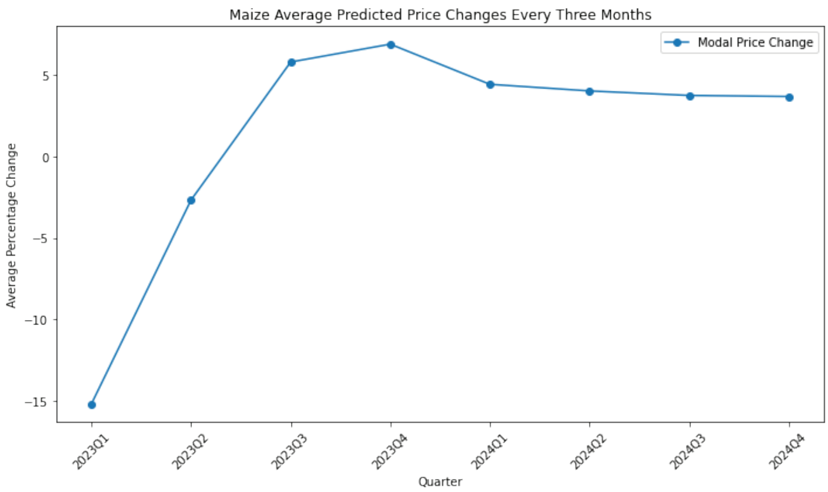

Figure 12. Average price change for maize.

Through Figure 12, the price change of maize can be averaged out over a specific time. It gives the visual depiction of price trends giving a clue on the changes to the prices and patterns that are important in understanding the market trend. Study of these changes can aid in decision making as far as maize cultivation and marketing concerns are concerned.

Figure 13 presented here indicates the average change in price of grapes which highlights the changes in the grape prices with time. Seasonal trends are important to market volatility, which can also help the growers and the traders in maximising their marketing and production measures. It is in knowing these price dynamics that profitability becomes the main area of focus.

Figure 14 represents the average change in prices of wheat and gives information about the temporal changes in prices of wheat. Looking at these changes, stakeholders are in a better position to determine the factors that pressure wheat prices and adapt their planning and operations in one way or another. This is an essential analysis to participate well in the market or risk management.

Figure 15 provides a view of average price change in ginger over an applicable time. Such information is vital because ginger producers and marketers need to monitor the market forces, future price expectation, and adopt strategic management prompted by the willingness to maximize profit and market competitiveness.

To demonstrate the changes in gram prices at each point in time, Figure 16 shows average price change in gram. Interpretation of such changes enables farmers and traders to predict the market, and devise their production Kuch IE

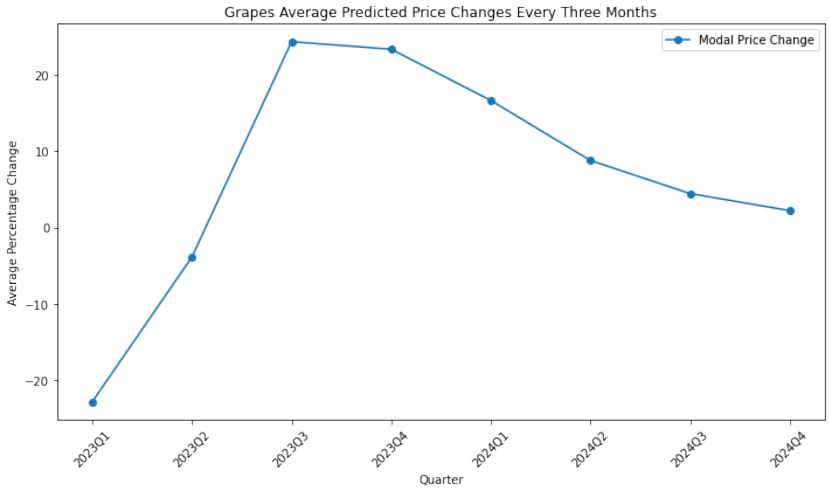

Figure 13. Average price change for grapes.

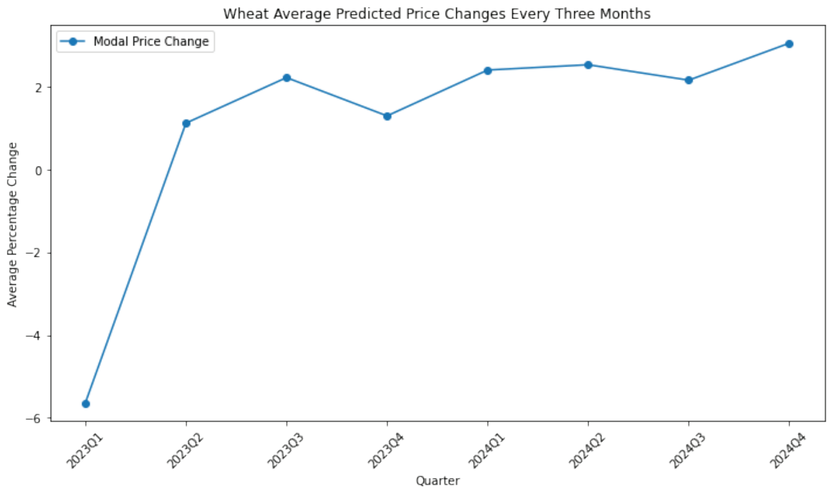

Figure 14. Average price change for wheat.

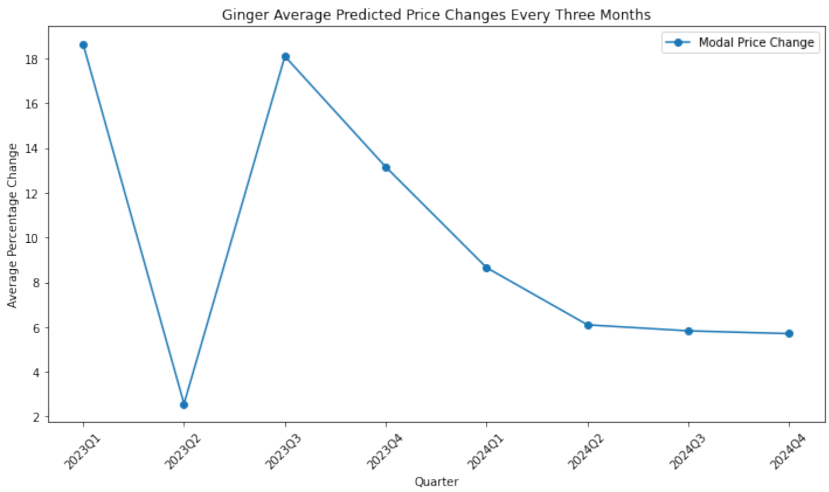

Figure 15. Average price change for ginger.

bates as well as design their sales strategies to obtain better economic returns.

Figure 17 illustrates average Jowar sales price change representing the change in the price over a specific period of time. The trends in the sector are critical to be analyzed by stakeholders in order to regulate supply chains efficiently and take necessary decisions that will fit market conditions and consumer needs.

The research involves the actual versus predicted least and the maximum prices of a series of crops over a quarter period using long short-term memory (LSTM) models. These crops have been selected as Jowar, maize, gram and grapes, wheat and ginger.

Tables 4-7 demonstrate how the LSTM models performed in each of the crop forecasting minimum and maximum prices. This quarterly breakdown identifies the overall prediction performance of this model overtime which can reveal the seasonality patterns or any market patterns.

Mal-predictions can be disastrous to the parties involved in the agricultural sector and thus accurate and precise predictions help in rational decision-making processes that can be used to subsidize on production, pricing, and the intervention process. In comparing the real prices and LSTM-predicted prices, it can determine the effectiveness of the models to pick the dynamism and fluctuation of prices in agricultural markets.

With this insight, hopes to contribute to gain traction in predictive analytics in the agricultural field, ensuring stronger supply chains and empowering farmers and policymakers to make informed decisions to drive sustainability in agricultural growth.

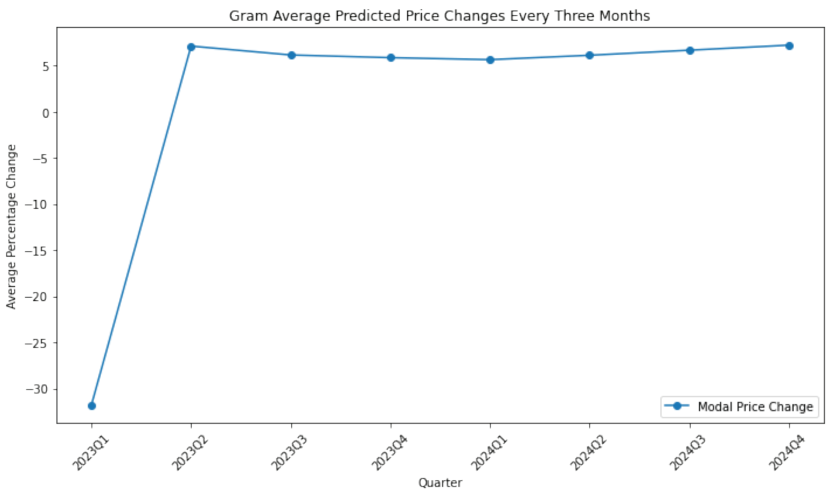

Figure 16. Average price change for gram.

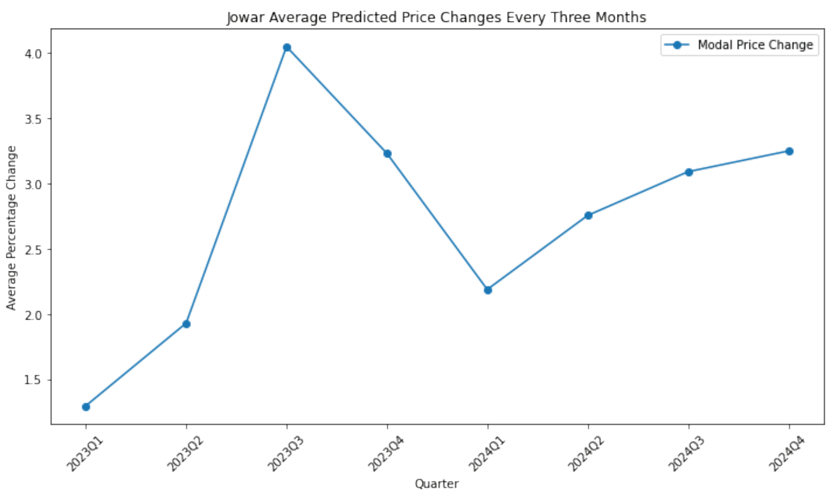

Figure 17. Average price change for Jowar.

Table 4. Actual vs. predicted price from January to March

Quarter 1	Actual Min	Predicted Min	Actual Max	Predicted Max
Wheat	4289.55	4357.412	5080.59	5631.452
Maize	2450	2138.38	2550	2424.48
Jowar	4634.32	4395.06	6313.42	4576.92
Grapes	2186.56	4844.94	12395.52	11828.98
Gram	5414.92	4649.72	5792.53	5900.63

Table 4 compares real vs. forecasted prices of Wheat, Maize, Jowar, Grapes and Gram between January and March. The LSTM models demonstrate a good predictive power especially in Wheat and Gram, which enables the farmers to plan better crop sales markets and their engagements therein.

As Figure 18 shows, the predictive model is accurate since it shows a relatively close parallel between the actual and the predicted prices during the period of January to the month of March. The correspondence between the actual and the predicted values signifies the level at which the model applies in predicting prices. It is these kinds of comparisons that are important in testing the model and enhancing the predictability of the model.

Table 5 shows the correlations between the actual and the estimated prices of the same crops in April, May and June. Compared to the LSTMs, the LSTM counterparts are more accurate in foreseeing the market conditions regarding Wheat and Maize and can serve the farmer as a predictive concept that would lead to appropriate responses in the area of strategic decision-making and financial benefit.

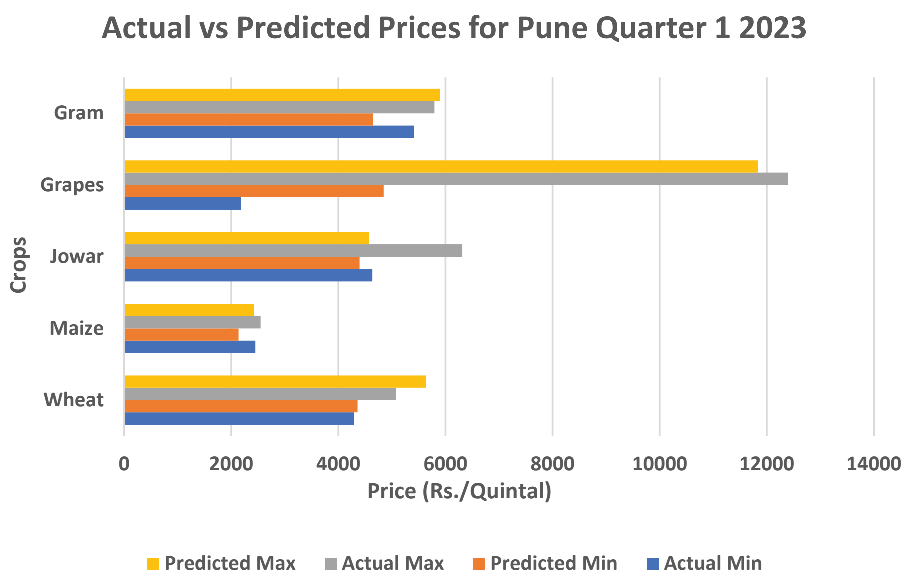

Figure 18. Actual vs. predicted price from January to March.

Table 5. Actual vs. predicted price from April to June

Quarter 2	Actual min	Predicted min	Actual max	Predicted max
Wheat	3936.36	4457.13	4854.54	5666.6
Maize	2450	2138.38	2550	2424.48
Jowar	4333.65	4402.3	5372.72	4581.35
Grapes	3192.98	5332.57	11763.15	12682.87
Gram	5473.68	5662.35	5832.89	5735.85

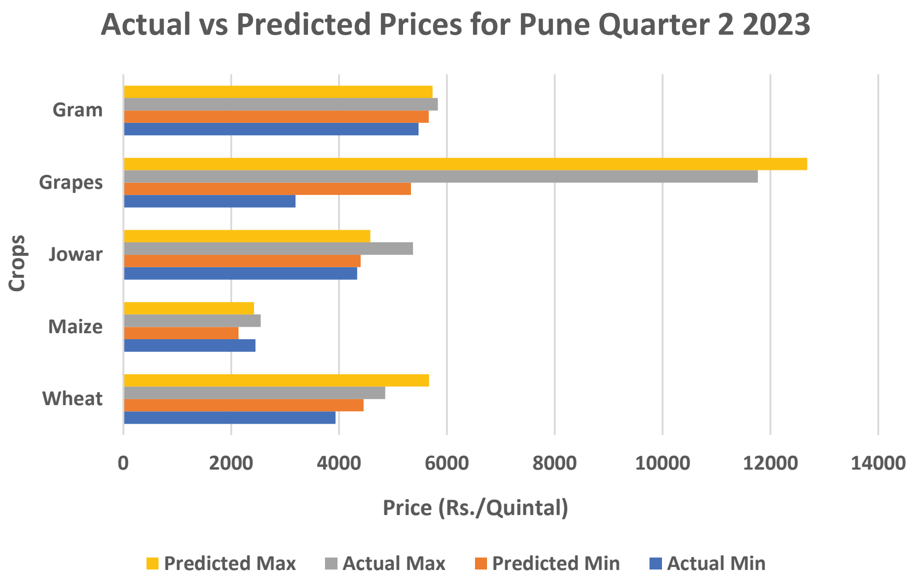

Figure 19. Actual vs. predicted price from April to June.

In Figure 19, the model forecast prices have been compared with actual prices between April and June indicating the way the model has performed over this period. The low difference between the actual and predicted prices shows the effectiveness of the model in capturing the trend in prices and eases the expectation of it being a powerful model making predictions relying on the past.

Table 6 presents the actual and the forecasted prices of crops between July and September. The LSTM models prove to be stable, especially in the case of Gram and Wheat, so that farmers can change their plans on production and sales operations depending on market tendencies in order to gain profits the most.

Various graphical representation is shown in figure 20 comparing actual and predicted price between July to September. The veracity of the model can be observed in the extent of similarity between the two groups of prices. Such observations play a crucial role in determining the performance of the model and making the relevant changes to boost or optimize its forecasting capacity.

Table 7 plots the comparison between the actual and forecasted minimum and maximum prices of Wheat, Maize, Jowar, Grapes and Gram between October to December. The LSTM models have contrasting accuracy ranging well above actual prices, Wheat and Maize and below, Grapes, where farmers can make informed market decision making.

It can be seen in Figure 21 that the comparison of actual and predicted prices is at an equal level. The figure assists in the assessment of the model in prediction performance during this period. Such precision in predictions as expressed through the comparison underlies the usefulness of the model in price forecasting in real-time so as to help in making improved decisions by agricultural stakeholders.

This paper augments the content of the review of actual and forecasted lows and highs of prices of major crops with visual analysis through the inclusion of bar graphs. Such graphs, based on Tables 4 to 7, provide a brief and user-friendly picture of the comparative performance of the LSTM models over time spanning quarterly periods. By comparing the actual prices with the LSTM forecast prices graphically, stakeholders are able to identify the accuracy and efficiency of the forecasting models over time easier Bronnenression się reasons stephen.

Table 6. Actual vs. predicted price from July to September

Quarter 3	Actual min	Predicted min	Actual max	Predicted max
Wheat	4257.89	4533.57	5256.57	5751.45
Maize	2400	2194.61	2500	2502.63
Jowar	5150.66	4404	6016	4582.2
Grapes	4032.25	6929.26	10919.35	17622.05
Gram	5773.68	6613.71	6189.47	6832.53

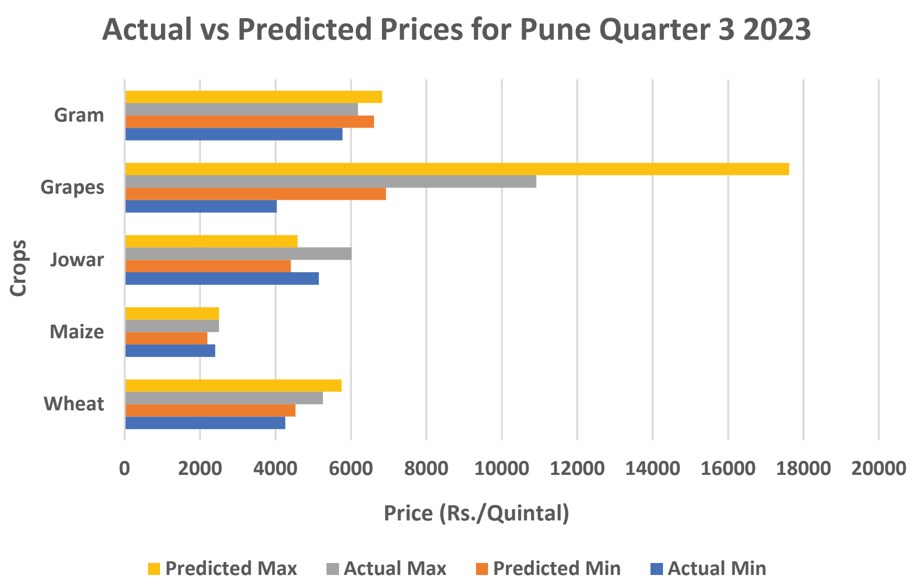

Figure 20. Actual vs. predicted price from July to September.

Table 7. Actual vs. predicted price from October to December

Quarter 4	Actual min	Predicted min	Actual max	Predicted max
Wheat	4384	4686.79	5464	5932.46
Maize	2500	2250.16	2650	2580.82
Jowar	5574.5	4404.56	6633.33	4582.51
Grapes	5000	8414.85	12750	22062.43
Gram	6381.94	7457.901	7393.05	7612.94

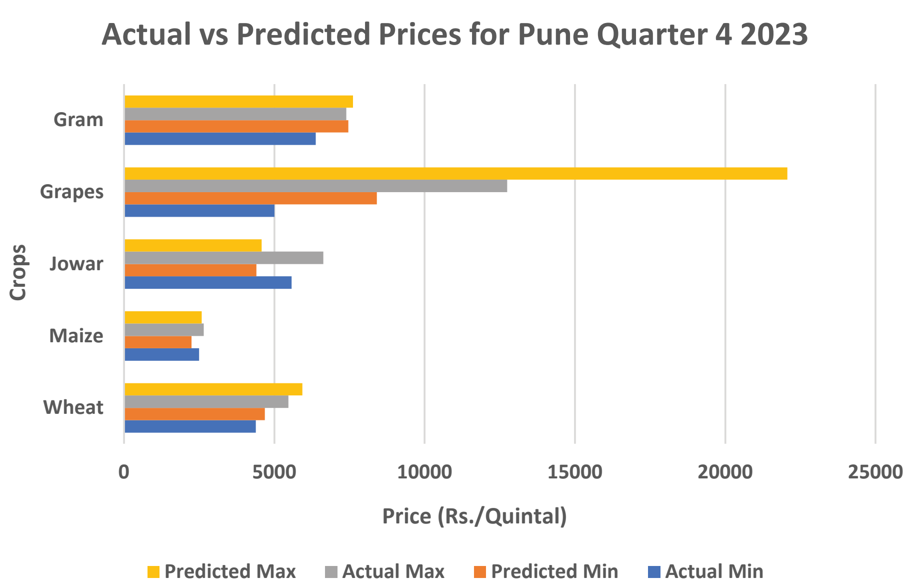

Figure 21. Actual vs. predicted price from October to December.

Bar graphs promote the readability of results and allow moving and comparing prices of various crops and quarters in a few seconds. Also, these visualizations play the role of an efficient communication tool, and complex analytical findings can be presented in a comprehensible and manageable way. Since bar graphs will be incorporated into this study, it will contribute to the better understanding of readers and, consequently, the better effectiveness of the conducted analysis, enabling the readers to draw practical conclusions related to agricultural decision-making and policy-making.

Overall Impact and Implications

Overall, the findings noted in the model forecast, the market value and the level of integration of the Internet of Things (IoT) reflect the dynamics of technological changes in the process of transformation. The program gives farmers custom recommendations, predictive data, and real-time monitoring and helps farmers overcome traditional obstacles, own and access permaculture benefits.

The adoption of technological products and services has enhanced the health status of the Indian farmers, improved their lives and also empowered the remote communities in the city. The program helps in preventing the weakening of agriculture due to the competition of this sector by enhancing precision agriculture and market-oriented agricultural approaches.

This dependence on both historical and real-time data presents a possible accuracy shortfall as a result of data quality problems, thus, impacting on model performance. The LSTM models, as much as they show great accuracy, still need to be refined more to give enough consideration to market dynamics and the conditions of the environment. Moreover, the technological framework that is needed an Internet of Things (IoT) implementation might not be easily available in the countryside, thus, precluding their large-scale usage. The way of scaling up to new crops and regions is problematic. It is recommended that future research looks into adding more detailed data sets, like satellite images and detailed weather predictions, to increase level of predictive accuracy. It is essential to further develop complex analytical tools, as well as use AI and blockchain technology to ensure greater data transparency and security, along with designing user-friendly interface design that would suit farmers. To ensure long term effects of long-term impacts of these intervention, longitudinal studies are also required as sustainable agricultural practices. The reviewed areas are the ones that should be worked on in order to promote the success of agricultural innovations and their inclusivity.

CONCLUSION

The work is responding to the high-priority problem of yield estimation in agriculture that preoccupies farmers and agriculture organizations conducts research, as well as uses state-of-art predictive modeling, and Internet of Things (IoT) technologies. The study is one of the milestones in the history of Indian agriculture breaking new ground to revolutionize the native culture and the introduction of the latest technologies. The study is achieved by blending machine learning, Internet of Things (IoT), and data science to take the most critical challenges of the Indian farmers and deliver actionable insights and new tools to them so that they can optimize their farming activity. The resultant predictive models are very accurate; they give a prediction of 99 percent accuracy when it comes to prescribing crops and fertilizers in accordance with particular soil and climate conditions. Not only does this increase agricultural yields but also increases sustainable farming because this will reduce dependency on the use of fertilizers.

By incorporating the Long Short-Term Memory (LSTM) networks into market price prediction (accuracy of 70-75 percent), the farmers will be provided with an opportunity to gain strategic option in relation to the choice of crops, plan harvests, and making market decisions. This predictive ability promotes profitability and reduces the risks of losses in case of financial losses, and farmers make clear decisions in a rapidly changing market environment.

Additionally, Internet of Things (IoT) monitoring equipment to determine the soil conditions in real-time is implemented, which gives valuable data about nutrients. This allows taking proactive nutrient control and the centralized platform that is developed with the Django framework supports the same. Its interface is easy and convenient to use, so farmers will have no difficulties using this technology.

It is a holistic manner of harnessing resources and not only maximizing use of resources but also creates economic stability in the rural economy. The use of new technologies in every farming aspect motivates the economy and its absorption potential because the farmers tend to survive in an adaptive world of agriculture.

To sum it all up, this study establishes a strong background of sustainable and efficient future of Indian agriculture. Data-driven intelligence and cutting-edge tools empower farmers to be prepared to handle and face the challenges of modern agriculture.

DATA AVAILABILITY STATEMENT

The authors confirm that the data that supports the findings of this study are available within the article. Raw data that support the finding of this study are available from the corresponding author, upon reasonable request.

CONFLICT OF INTEREST

The author declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

ETHICS

There are no ethical issues with the publication of this manuscript.

STATEMENT ON THE USE OF ARTIFICIAL INTELLIGENCE

Artificial intelligence was not used in the preparation of the article.

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