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Enriching Crop Yield and Price Prediction Using Transformers

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***Abstract*: Most developing and underdeveloped countries rely heavily on agriculture and its byproducts for their economic growth. The farmers of these countries hugely rely on the weather to get a good crop yield; due to global warming, there have been a lot of changes in the weather, which leads to untimely rain or no rain at all, extremely windy, cold, and many types of harsh conditions. Because of all this most of the farmers lose the good crop yield leads into a hand-to-mouth situation for farmers and in some worst cases, may lead to the suicide or bankruptcy of the farmers in a country like India. Artificial intelligence plays a crucial role in predicting crop yield and market price before seeding, which can ultimately improve farmer's living standards by enhancing agricultural practices and making the right decisions. Usually, we use machine learning and deep learning models to predict crop yield and market price individually; hybridizing these models could potentially yield better results by the usage of transformers with deep learning mechanism. Therefore, the designed model utilizes the dataset of crop yield and price, applying temporal fusion transformers to obtain precise predictions. The obtained results of RMSE are scrutinized to check the authenticity of the fusion of neural networks.**

***Keywords*: Neural Networks, Deep learning, Transformers, Crop yield prediction, Crop price prediction, Alternate crop suggestions.**

1. Introduction

As we all know, the majority of citizens in most developing and underdeveloped countries rely on agriculture as their primary source of income. Hence, it affects the government, people's lives, the stock market, and even the banking sector. So, to keep the agriculture sector in proper shape, which can yield the crops to their best, the government does take numerous measures. These measures generally include providing subsidized seeds, fertilizer, crop insurance, and many more to the farmers. The government needs to do all these things to uplift the farmer's life by improving their agricultural tactics and providing good maximum retail prices for their grown crops. This will ultimately play a significant financial burden on government agencies, particularly if the number of farmers increases significantly, as it does in India.

Therefore, artificial intelligence plays a crucial role in aiding farmers, the government, and other organizations by accurately predicting crop yield before sowing and also forecasting crop price. These two major predictions have the potential to significantly improve the lives of farmers and assist the government in managing farming budgets. Artificial intelligence assists numerous stakeholders from various perspectives by predicting crop yield. Crop yield predictions can assist farmers in determining the exact yield under specific conditions, allowing them to choose alternative crops to avoid potential disasters. A precise prediction of the crop yield can help farmers use the right amount of pesticides and fertilizers to avoid unnecessary waste. Farmers can effectively manage water management through efficient irrigation scheduling, which not only saves water but also ensures optimal plant growth based on early crop predictions. Early crop predictions can assist farmers in effectively managing their workforce to meet seasonal demands. Accurate yield estimates can help farmers file insurance claims more effectively in case of crop losses due to natural disasters or pests. Farmers can anticipate market trends and adjust their production accordingly. Due to crop predictions Governments can assess food security by monitoring crop production and potential shortages.

Crop price prediction is a valuable tool for various stakeholders in the agricultural sector, including farmers, traders, policymakers, and consumers. By predicting crop prices, farmers can make informed decisions about which crops to cultivate, when to plant and harvest, and how much to sell based on projected prices. By anticipating price fluctuations, farmers can better manage risks associated with production costs, market volatility, and potential losses. Accurate price predictions can help farmers optimize their production strategies to maximize profits. Even crop Traders can make strategic decisions about buying and selling crops at the right time to capitalize on price trends. Crop price predictions can inform economic planning and development strategies, particularly in agriculture-dependent regions. Because of early crop price prediction, consumers can be aware of potential price fluctuations and make informed decisions about their food purchases. We can develop accurate crop price prediction models to benefit various stakeholders in the agricultural sector by considering these factors and leveraging advanced data analysis and machine learning techniques.

Time series analysis and linear regression, two examples of traditional statistical models that consider historical trends and seasonal patterns, also aid in crop yield predictions. Machine learning models like Random Forest, which combine numerous decision trees to enhance accuracy, also aid in efficient agricultural production prediction. In contrast, neural networks

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mimic the way the human brain learns and makes predictions, while support vector machines (SVMs) analyze data for complicated patterns. Therefore, the suggested model employs the Temporal Fusion Transformer (TFT) to achieve more precise outcomes. As a rule when it comes to machine learning, a transformer is a neural network design that can learn context and create new data by analyzing sequential input. Using a combination of recurrent layers to learn local dependencies and self-attention techniques to capture long-term dependencies and feature interactions, the TFT is specifically developed for time series forecasting. Because of this, it is ideal for dealing with agricultural data, which consists of intricate linkages.

The interaction regression model for predicting agricultural yields was introduced by Javad Ansarifar et al. [1] and it has three main improvements. To start, in a thorough case study, its prediction accuracy was higher than that of state-of-the-art machine learning methods. Secondly, it discovered around twelve E × M interactions for corn and soybean yield that are temporally and spatially resilient, allowing for the formation of counter-intuitive, insightful, and testable hypotheses. Third, it clarified how factors like weather, soil, management, and interactions between the three affect harvest success. Improving prediction accuracy and making more biologically and ergonomically insightful discoveries could be achieved by integrating additional data in future studies. This could include high-dimensional genotyping data, plant attributes, comprehensive management plans, and satellite pictures, among other things.

[2] According to Uferah shafi et al., predicting wheat crop yields accurately and in a timely manner is crucial for ensuring food security on a worldwide scale. With that goal in mind, this paper presents a methodology for predicting wheat grain production. Using drone-based sensors, researchers gather multispectral data covering the entire crop life cycle from three separate experimental fields. The wheat crop is sown into each field at a different time. Using multispectral data and machine learning approaches, wheat grain yield estimation is now being done. Nevertheless, the author intends to investigate deep learning methods such as CNN, LSTM, etc., for the purpose of analyzing optical data collected by drones in order to predict future agricultural yields. To further improve the precision of yield estimation, the authors intend to incorporate additional variables such as soil and climatic data.

[3] According to A. Reyana et al., one of the most important parts of India's economy is farming, which is feeling the pinch from things like drought, unpredictable weather patterns, and inefficient methods of water management. In order to help farmers make decisions regarding improving crop production, the current study is available. When it comes to agriculture text classification, experiments on the benchmark dataset reveal that the random forest approach achieves the lowest error measure, with RMSE 13%, RAE 38.67%, and RRSE 44.21%. More accurate predictions are made possible by a multi-sensor data fusion method that is based on crop suggestion, leading to a notable uptick in agricultural output and more visibility for the condition-based environmental monitoring system. Methods that account for all agricultural field factors should be considered for future research to improve prediction. Consequently, the random forest method achieves very good accuracy and a low rate of error while classifying the agricultural dataset.

Section 2 of the article outlines the prior research, and Section 3 describes how the proposed model is implemented using the temporal fusion transformer. Following a discussion of the obtained results in Section 4, the research is concluded in Section 5. Future research on this area is discussed in Section 5.

2. Related Works

[4] The purpose of this study by Vasileios Balafas et al. is to review the literature on plant disease detection and classification approaches that make use of ML and DL techniques in precision agriculture. Furthermore, a novel system of categorization is presented, which assigns appropriate labels to all pertinent publications. Based on the methods used, the author divides the investigations into two primary categories: classification and object detection. In addition, the author lists the datasets that are currently accessible for plant disease classification and detection, describes each dataset in depth, including what classes it belongs to, what data it contains, and whether or not it is good for object detection or classification. The author intends to investigate further categorization and object detection methods on more datasets in future work to determine if the outcomes are consistent across various datasets. The author also plans to investigate data augmentation and image preparation methods to determine if they can enhance the algorithms' accuracy.

[5] Mamba Kabala Denis et al. The field of crop disease classification using machine learning technologies is constantly developing, with a focus on CNN and ViT-based systems. While there are several benefits to federated learning (FL) in terms of user data security and sensitive data retention, this new paradigm has received little attention in this field until now. The author of this study set out to change that. The efficacy of ResNet50 in multiple experiments further emphasizes the importance of selecting the machine learning model architecture most suitable to FL scenario. Author can learn more about how to use FL for crop disease classification because to this study. Therefore, to further investigate these findings and other FL-related agricultural disease classification needs, additional research is required.

[6] According to Pritesh patil et al., predicting agricultural yields is no easy task because it depends on a myriad of variables such as soil, weather, fertilizers, pest infestations, and more. This paper uses meteorological and soil factors to forecast crop yield. Only datasets pertaining to districts in Maharashtra were used for the research. The system uses multi-class classification to forecast crop type and regression methods to estimate yield.

[7] According to Alejandro Morales et al., machine learning algorithms have little success (compared to a meaningless average-yield baseline) in forecasting sunflower and wheat yields across several regions of Spain. Underestimating model mistakes occurs when data is randomly partitioned for testing

and training instead of being time-dependent. While ANN and linear models do not guarantee accuracy in the absence of enough data, RF is always at least as good as the best guess estimate, which is the average of the farm production based on historical data, and it is also easier and faster to run.

[8] The authors of the study include Kavita Jhajharia et al. Machine learning methods such as Random Forest, Support Vector Machine (SVM), and Lasso Regression clearly surpass deep learning models like Gradient Descent and Long Short-Term Memory (LSTM) when it comes to accuracy, according to all the discussions and evaluations. This might be due to the fact that higher-quality prediction analyses from models like LSTM necessitate a bigger quantum of data compared to competing algorithms. In addition, the data shows that most models work better with the given parameters, but that models like Gradient Descent and Lasso Regression shine when given the complete dataset.

[9] By creating a state-of-the-art 3D-CNN ConvLSTM ViT model for precise crop yield prediction, the work of Seyed Mahdi Mirhoseini Nejad et al., as detailed in this article, significantly advances precision agriculture. The significant improvement in RMSE, which indicates a more accurate yield prediction than state-of-the-art models, is a reflection of the model's capacity to handle multispectral remote sensing data. This improvement demonstrates how the model may lead to more accurate and well-informed farming methods, which in turn can help achieve sustainable agricultural development.

[10] Using Landsat 8 remote sensing imagery and the RF, LASSO, and SVM ML methods, Muhammad ashfaq et al. sought to determine the best model, data sources, and spectral band combination for estimating winter wheat yield. By comparing the three models' temporal relationships with satellite data and winter wheat production, Author find that the RF model achieves an astounding 97% accuracy, well surpassing SVM and LASSO. Central Punjab and the Pothohar region are two examples of agriculturally dependent areas that might be officially included in the study's expansion. Additional research on the effects of floods, waterlogging, salinity, and other variables on wheat output is planned for the near future.

[11] In their recent work, Md jiabul hoque et al. provide a framework for agricultural yield prediction using an optimal gradient boosting ML model. In the particular context of India, the framework has been designed with the express purpose of growing important crops including sorghum, sweet potatoes, rice, wheat, potatoes, and soybeans. The study was carried out successfully by incorporating data from credible sources, such as the United Nations FAO and the World Bank's Climate Knowledge Portal. Acquiring this data required scouring numerous databases for details regarding farming, insecticides, and climate. A more streamlined process and greater efficiency were the outcomes of integrating these disparate data sources using Extract, Transform, and Load (ETL) techniques.

[12] The crop recommendation models created by Abid badshah et al. employ state-of-the-art machine learning techniques to ascertain the optimal crops for planting. Because of its scalability and adaptability, this method can be easily applied to other data sets and different regions. Explainable artificial intelligence (XAI)-based agricultural advising systems also enhance trust and transparency. XAI provides clear understanding of model choices by showing how variables like soil pH and rainfall impact recommendations. This transparency promotes confidence among users and aids farmers in making more informed decisions. In addition, XAI ensures accountability, helps users learn about the importance of various crop selection aspects, and highlights potential biases, all of which contribute to AI insights being used more efficiently.

[13] Using basic ML techniques with accumulated heat data and an RF regressor, Alakananda mitra et al. accurately forecasted cotton yields in several U.S. locations. One unique aspect of this work is the way it reduces computational effort while maintaining model accuracy by transforming time-series weather data into a scalar value, AH. In addition to the RF regressor, the author presented the LightGBM regressor, a competing ML technique. Training on massive datasets improves the performance of machine and deep learning algorithms. Nevertheless, ML/DL-based methods aren't always usable because huge publically available datasets aren't usually accessible. While using synthetic data to train AI/ML models is a typical approach for dealing with data shortages, it is not commonly employed in the agricultural sector. Author developed and evaluated an AI-based cotton model using both synthetic and real-world data. This strategy will be expanded to more sites in the southern cotton belt of the United States and then applied on a regional and national scale as part of the author's future study. The author will also strive to prove the method's validity by applying it to other crops in the US. Because of this study's high level of accuracy, the author thinks that other researchers will be more motivated to utilize synthetic data to create AI-based crop models, which will help bridge the gap between the agricultural industry and cutting-edge technology.

[14] With the use of enhanced loss functions integrated into FNNIS, Amna ikram et al. shows that yield prediction in pea-cucumber intercropping systems may be improved. Intercropping systems are complicated and dynamic, and traditional methods that rely only on the MSE loss function do not understand them. As an added bonus, the suggested method uses DML, RAL, QL, and HAEL to withstand many kinds of prediction mistakes, including risk, uncertainty, and applied relevance.

[15] An effective detection technique based on an upgraded YOLOv5s is proposed in this paper by Wei chen et al., which allows for accurate identification of prevalent crop diseases. Before the model could learn and extract all leaf features, the third, sixth, ninth, and twelfth layers of the backbone network were enhanced with SE attention mechanism modules. In order to improve the model's ability to extract features in diseased areas and accurately distinguish between different types of crop diseases, the author first swapped out the YOLOv5s model's original up-sampling operator with the Content-Aware Reassembly of Features (CARAFE) up-sampling operator. This new operator can obtain more accurate up-sampled feature

maps.The author continued by enhancing the model's performance by substituting the EIoU loss function for the original YOLOv5.

[16] Three separate models were examined by Rahul Kumar et al. for their predictive capabilities: Support Vector Machine (SVM), MultiClass SVM, and an Ensemble Model that incorporates Decision Tree and Random Forest techniques. The author's goal was to classify inputs as either "Diseased" or "Healthy" in the binary classification challenge. The author assessed the models' confidence in making predictions by looking at both their class predictions and the related class probability estimates. Without a single exception, all three models predicted that the input would be "Diseased." But what really set them apart were the degrees of certainty expressed by their class probability estimations.

[17] Researchers Xiaotong Yao et al. In light of the characteristics of wheat diseases—such as less distinction and more complex morphological and color aspects—this study presents YOLO Wheat, an algorithm for identifying wheat diseases. The dataset was generated using photographs of wheat diseases that were obtained independently, and the main conclusions of the study are summarized here. For wheat disease databases to be accurate and reliable, they need to be custom-completed in natural settings.

[18] In According to Mahmoud Abdel-salam et al. Among the most difficult fields to apply analytical findings is agriculture. Agricultural output and precision farming are impacted by environmental factors such as soil quality, pest infestations, crop diseases, and weather. The use of machine learning in agricultural yield forecasting has the potential to revolutionize the industry. Machine learning models evaluate evidence, transform data, and impart extensive process expertise.

3. Designed Model

The designed model for the prediction of crop yield and Price is depicted in the above figure 1. The steps that are undertaken to achieve the designed model is elaborated in the below narrated phases.

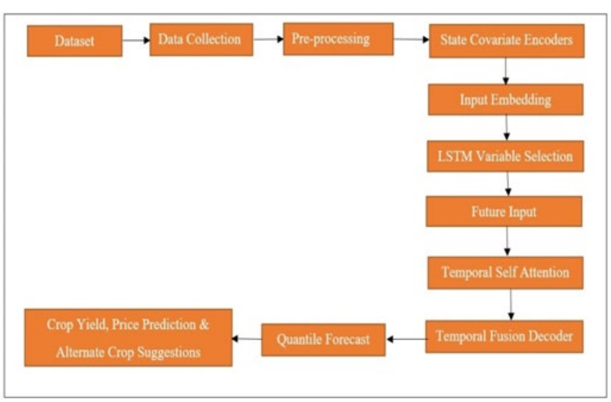

Fig. 1. Proposed model design

A. Phase 1: Data Collection

The crop yield prediction method was implemented using a Crop dataset that was downloaded from https://www.kaggle.com/datasets/atharvaingle/croprecommendation-dataset/data. We are going to employ this dataset and feed it into the suggested method to find the crop yield. The gathered dataset is loaded into the proposed approach for making predictions. Working with the pandas and csv libraries, the program opens the dataset in a workbook format. This module allows Python programs to interact with workbook files.

In recent decades, precision agriculture has become increasingly popular. Better decisions on farming tactics can be made by farmers in this way. With the data in this dataset, users can build a predictive model that, given some parameters, can inform farmers which crops would do best on their individual fields. Here are the factors that make up this dataset for agricultural yield prediction:

- N - ratio of Nitrogen content in soil
- P - ratio of Phosphorous content in soil
- K - ratio of Potassium content in soil
- temperature - temperature in degree Celsius
- humidity - relative humidity in %
- ph - ph value of the soil
- rainfall - rainfall in mm

It is common practice for the dataset to be utilized after acquisition in the pre-processing step. Reading the dataset from the specified path and gathering its properties into a two-dimensional list is what this pre-processing step is all about. Pandas, a Python package, was used to read the dataset from the specified directory. The initial parameters of the attributes are estimated using this data from a two-dimensional list.

B. Phase 2: Dataset Preprocessing

To characterize the features of the dataset, such as its mean and standard deviation, these two-dimensional list data are utilized for estimating the early parameters. Following this step, the entropy of the dataset's data types—such as strings and floats—is asserted by obtaining information about the dataset's attributes. The oversampled data is used to estimate a heat map for each characteristic. This is accomplished by calculating the total amount of missing data and the percentage of that data that is missing by comparing the transition data throughout the sorting process. Attributes such as N, P, K, Ph, and countless more have their missing values imputed using the fillna() method. For each object in the attributes, a label encoder is used as a formal argument with the fit transform function for imputation. The IterativeImputer() function is utilized to implement multiple imputation using chained equations, resulting in the object of mouse imputation. This is then used to impute the missing attributes, after the transformation of the characteristics using the fit transformer.

C. Phase 3: Encoders and input embedding

This particular phase of the process involved the application of encoding to category features such as Crop, Season, and State. Standard Scaling was utilized in order to produce standardized numerical features by using the minmax scalar function. The minmaxscaler to change the features, scale them to a certain range. This estimator applies separate scaling and translation to each feature in order to get it inside the specified range on the training set, for instance, between 0 and 1. The effect of outliers is not mitigated by MinMaxScaler, even if it linearly scales them into a predetermined range, with the biggest data point representing the highest value and the smallest the minimum. Consult to see how MinMaxScaler is visualized, compare it to other scalers. Solving equations 1 and 2 yields the minmaxscaler transformation.

$$x_{std} = \frac{(x - x.min(axis=0))}{(x.max(axis=0) - x.min(axis=0))} \quad (1)$$

$$x_{scaled} = x_{std} * (max - min) + min \quad (2)$$

where min, max = feature_range.

Following the encoding of these attributes, they are subsequently incorporated back into the double list of the attributes that make up the dataset.

D. Phase 4: LSTM model

Our data is divided into a train set and a test set using the train_test_split() function. First, we need to sort our data by features (X) and labels (y). The y_train, y_test, X_train, and X_test components make up the dataframe. The X_train and y_train datasets are utilized for training and fitting the model. See if the model gets the labels and outputs right by using the X_test and y_test sets. Explicit testing of the train and test set sizes is possible. It is recommended that we keep the train sets bigger than the test sets.

LSTM neural networks take a scalar normalization object, test_x, train_x, and test_y as inputs. To introduce the LSTM model, which uses a one-dimensional space with a single feature, ten units of samples, and a TRUE return sequence, a few parameters such as train_X1.shape [1] and train_X1.shape[2] are needed. Next, we add a Dense layer that uses the "relu" activation function and has a kernel size of 1. In a densely coupled neural network, the activation functions of neurons are utilized by the dense layer to efficiently acquire new knowledge. In this example, we use a single kernel of size 1 with one-dimensional data, while the fundamental LSTM neural network consists of two dense layers. A neural network is constructed with a batch size of 100, 100 epochs, and the shuffle parameter set to false.

The equations 3 and 4 below display the ReLU and Sigmoid functions respectively.

$$f(x) = max(0, x) \quad (3)$$

Where, x is any positive value

$$S(X) = \frac{1}{(1+e^{-x})} \quad (4)$$

Where,
X is the input to a neuron
f(x) = Relu Activation Function
S(x) = Sigmoid Activation Function
e= Euler's Number

E. Phase 5: Temporal Fusion Transformer

We deployed a Temporal Fusion Transformer (TFT) to improve the precision and comprehensibility of forecasts for agricultural yields. Using a combination of recurrent layers to learn local dependencies and selfattention techniques to capture long-term dependencies and feature interactions, the TFT is specifically developed for time series forecasting. Because of this, it is ideal for dealing with agricultural data, which consists of intricate linkages. As part of the TFT design, the model relies on static covariate encoders to process features that remain constant across time. A high-dimensional representation of numerical and categorical information can be achieved by input embeddings. In order to process inputs from the past and future, the model employs long short-term memory (LSTM) encoders, which record short-term dependencies, and LSTM decoders, which forecast future states. At each time step, traits that are most relevant are dynamically selected using variable selection techniques.

The temporal self-attention layer is the brains of the TFT; it captures long-term interactions and dependencies between various time steps and characteristics using masked interpretable multi-head attention. In order to stabilize and manage the flow of information, the Temporal Fusion Decoder uses Gated Residual Networks (GRN) and position-wise feed-forward networks to integrate these processed inputs. Quantile forecasts, which give a probabilistic range of potential outcomes, are generated by dense layers. To avoid overfitting, training employs the Adam optimizer, mean squared error loss, and dataset partitioning into training, validation, and test sets.

TFT works on the basis of the following architecture as mentioned in [19] and depicted in figure 2. Once the temporal fusion is decoded the perdition for crop yield along with the price is obtained with the suggestion for the alternate crop.

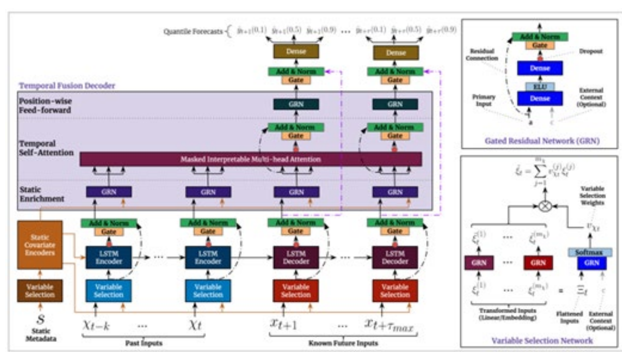

Fig. 2. TFT architecture

4. Results and Discussions

A Windows-based G6 machine deploys the designed approach to predict crop yield and price using the deep learning model LSTM and transformer TFT. A 1 TB secondary memory device and 16 GB of RAM power the machine. The designed model successfully carried out a set of experiments to estimate the error rate of crop yield and price predictions. The process incorporates root mean square error(RMSE), a continuous error between the observed predictions and the obtained prediction value in each experiment. The below-mentioned equation 5 indicates that the working of RMSE based on the depicted attributes

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}\left(x_{1,i} - x_{2,i}\right)^2}{n}} \quad (5)$$

Where,
$\sum$ - Summary
$(x_1 - x_2)^2$ – Difference between the Squared for the observed and obtained predictions
N - The number of trails

The proposed approach for predicting crop yield and price, as well as the suggestion, is tested through a series of ten trials to ensure its validity. The number of accurate.

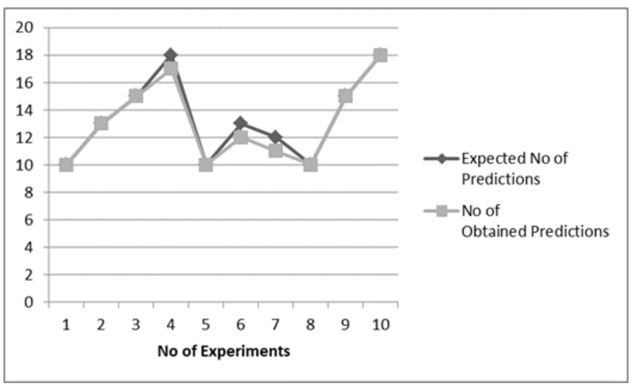

Fig. 3. Comparison of mean square error for each experiment

predictions obtained compared to the predicted number of forecasts was documented in these trails. Figure 3 shows the resulting graph of the trails.

We may conclude that this method for estimating crop yields achieved an insignificant degree of inaccuracy after conducting a thorough review of the facts presented in tabular and graphic representations. At first, we ran a series of 10 trials with N number of experiments altering input in order to find the Mean Square Error, or MSE. The empirical investigation indicates that the prediction system has a moderate and acceptable error rate. Typically, the estimation methods that can detect any errors in the prediction are the ones that use real-world data to generate predictions. Many factors influence the prediction of the crop yield and price predictions. Hence, the designed model is compared the obtained results with that of [20]. The proposed model utilizes the temporal fusion transformer technique to obtain the crop yield and price predictions. The experiments above yield a mean square error (MSE) of 0.3 and a root mean square error (RMSE) of 0.547. The obtained values are comparable to those reported in [20].

As stated in [20] Anıl Suat et al. outline Global economies are directly affected by the difficulty of predicting agricultural yields, which is of paramount importance for food management and security. Recent advances in image classification using deep Convolutional Neural Networks have brought deep learning to a point where it might be applied to agricultural monitoring, crop type classification, and systems for estimating crop yields. Conventional methods for predicting agricultural yields using remote sensing rely on classical machine learning algorithms like Decision Trees and Support Vector Machines. Models for Convolutional Neural Networks (CNNs) and Long-Short Term Memory Networks (LSTMs) are among the deep neural networks that have recently been proposed as potential crop yield predictors. The researchers in this study set out to create a 3D CNN model that could predict soybean harvests in Lauderdale County, Alabama, USA, by utilizing spatiotemporal data. The USDA NASS Quick Stat tool is used to derive the yield for the years 2003–2016. Google Earth Engine processes satellite photos taken by NASA's MODIS system to produce surface reflectance, temperature, and land cover data. The results can be compared to other methods that often use RMSE as their evaluation metric by using RMSE as the assessment metric.

The comparison of obtained MSE and RMSE by our methodology and of [20] is tabulated in the below table 1 and respective graph can be depicted in figure 4.

Table 1
Comparison of MSE and RMSE between TFT and CNN [20]

Methodologies	MAE	RMSE
TFT (Our approach)	0.3	0.547
CNN based as in [20]	0.656	0.81

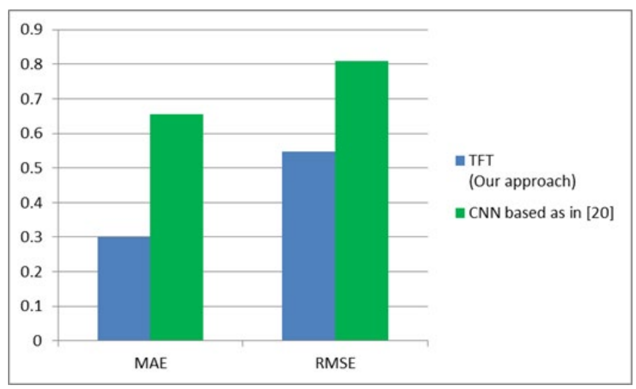

Fig. 4. MSE and RMSE comparison between CNN [20] and TFT

The graph in figure 4 clearly illustrates the proposed approach, which uses LSTM and temporal fusion transformer on a time series dataset to accurately predict crop yield and price, resulting in an MSE of 0.3 and an RMSE of 0.547. These obtained data is better than the MSE of 0.656 and the RMSE of 0.81, as mentioned in [20]. This is purely due to the use of a time series model in hybrid mode.

5. Conclusion and Future Scope

This paper proposes a method of using a temporal fusion transformer on a crop yield and price dataset to predict the yield and price for the given date. The proposed system, for deployment purposes, uses a dataset that includes attributes such as soil type, nitrogen quantity, phosphorous quantity, potassium quantity, soil pH value, rainfall, humidity, crop, wind speed, and more. Once we obtain the dataset, we preprocess it to extract the required data into a double-dimension list. Then the obtained double-dimension list is imputed using the MICE imputation process. The encoders then use the minmaxscaler function to convert the imputed data into a numerical value. An LSTM model is deployed in the encoded data to obtain the trained model, which is used by the temporal fusion transformer (TFT) efficiently. TFT uses a look-back window of a predetermined length to pull target values from the past. Next, TFT constructs the unknown input from permutations, forming time-dependent external input features. Finally, TFT utilizes static covariates to provide time-independent contextual metadata about the entities under evaluation. This integration allows the developed model to provide precise predictions about crop output and price. The measured results provide MSE of 0.3 and RMSE of 0.547 which are far better than the compared model of CNN. More extensive crop predictions covering larger areas, such an entire country or state, may be possible in the future thanks to well-planned scientific investigations. One possible improvement to the technique is to make it work as a smartphone app. This would make it easier for government agencies and farmers to access the data through cloud deployment of the model.

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