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A Novel Approach for Crop Yield Prediction based on Hybrid Deep Learning Approach

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***Abstract* – The agricultural sector is crucial to the economic development of our country. Civilization's birth was facilitated by agricultural practices. The agricultural sector is vital to India's economy because of the country's status as an agrarian nation. So, agriculture has the potential to serve as the economic foundation of our nation. In agriculture planning, crop selection is crucial. Our Indian economy desperately needs widespread reforms in the agricultural sector. In this proposed approach to use several machine learning methods to forecast future agricultural yields. After receiving the input image, the null values can be filtered out using the preprocessing approach. The Relief method is then used to choose features. In order to extract features, a linear discriminant analysis approach is used. Finally, the CNN-BiLSTM-ECA model, which combines a CNN, a Bidirectional Long Short-Term Memory network, and an Attention Mechanism, is presented for use in training (AM). To reduce the impact of excessive noise and nonlinearity, CNN has been used to extract deep aspects of agricultural productivity. Crop yield is predicted using a BiLSTM network trained on the recovered deep characteristics. This proposed also implement an unique Efficient Channel Attention (ECA) module to increase the network model's sensitivity to key features and inputs. The average error made by each method is compared to one another. Farmers will be able to use the CNN-BiLSTM-ECA forecast to guide their planting decisions by taking into account variables like expected temperatures, precipitation, available land, and more.**

***Keywords*—Convolutional Neural Network (CNN), Attention Mechanism (AM), Efficient Channel Attention (ECA).**

I. INTRODUCTION

Agriculture is crucial to human progress since it produces a majority of the world's food supply. Many countries still struggle with hunger as a result of rising populations and inadequate food supplies. One promising approach to ending hunger is to increase food production. In order to make educated judgments about food exports and imports, policymakers in a country want reliable forecasts. The world's ability to feed itself depends on our ability to accurately predict crop yields. Improving the nation's food security requires prompt policy decisions to import and export based on accurate forecasts Seed companies can't increase harvest yields without reliable information about how new hybrids will fare in varying climes. However, due to the many complex factors involved, it is extremely challenging to predict agricultural yields. High-dimensional marker data, which often includes thousands upon thousands of markers for each plant individual, is used to represent, for example, genotype information. Farmers who were ahead of their time were already employing the practices that would later be categorized as precision agriculture. They identified the causes of yield variance in their fields and developed plans to address these issues. This was achieved by farmers keeping meticulous records of their fields throughout the planting, tending, and harvesting seasons so that they could better prepare for the coming year. Nonetheless, [1]discovered that data-generating tools and sensors are becoming more widespread in agriculture, providing farmers with the ability to make decisions supported by data. Predicting crop yields accurately in the months leading up to harvest is a key part of solving food security problems. In the face of climate change and droughts, agricultural surveillance, especially in underdeveloped nations, can increase food production and aid humanitarian operations[2]. Making the world more food secure includes actively and critically predicting CROP yields. Attempts to anticipate crop yields reliably and in time for harvest have been pursued for decades. Cultivation yield projections have traditionally been made using crop simulation models (CSMs) [3]There are two main problems with using CSMs to forecast crop yields. Second, the enormous number of indicators needed for calibration severely restricts the applicability of such models. Second, as CSMs are often developed for particular regions based on situations of current relevance, it is difficult to make accurate predictions of yields in other countries. Many models have been presented and proved so far, but estimating crop yields remains one of the most difficult problems in precision agriculture. Many factors, such as soil, climate, fertilizer use , weather, and seed variety, impact agricultural yield, necessitating the use of multiple datasets to find a solution [4]. This indicates that calculating expected crop yields is a complex, multi-step procedure. Models can predict agricultural yields fairly well these days, but more precise predictions are always desired. Improving food security and ensuring a sufficient food supply necessitate accurate predictions of crop yields. This task must be carried out accurately on both a national and regional scale if prompt decisions are to be made. For instance, it is considerably simpler for policymakers to decide whether or not to import or export specific items if the findings of crop production forecasts can be trusted. Farmers can benefit economically from this type of forecast. Companies that specialize in selling seeds can also evaluate how well new types perform in a range of conditions. The proposed approach has four phases such as preprocessing, Feature Extraction, Feature Selection and finally it is utilized to train the model using a CNN-BiLSTM-ECA approach.

II. LITERATURE SURVEY

[5]reviewed the research on nitrogen status estimation using machine learning and published their findings The paper also notes that rapid advancements in sensing technology and ML methods will lead to cost-effective solutions in agriculture. The soil composition and, by extension, the quality of the agricultural production, are profoundly affected by air quality, weather and temperature, and air quality fluctuations. Therefore, it is incumbent upon the current generation to devise methods of mitigating the unfavorable effects of environmental repercussions on agricultural production. Predicting crop yields continues to attract a lot of interest from scientists all over the world. A deep learning system for remote sensing-based agricultural production prediction was presented by you and colleagues [6].For the purpose of predicting annual crop productivity in largely poor nations, the method employed a Convolutional Neural Network (CNN) with a Gaussian process component and a dimensional reduction methodology.[7]discussed the effects of yearly fluctuations in rice prices on farmers' incomes and quality of life. If farmers and other stakeholders could more reliably predict agricultural productivity under various climatic conditions, they could use that information to make better agronomic and crop selection decisions. Several districts in the Indian state of Maharashtra can have their rice yields predicted by a neural network, and the factors that affect those yields can be analyzed. The author used artificial neural networks to forecast rice harvests in the Indian state of Maharashtra and evaluated their performance. Modeling time series with remote sensing data is a relatively recent field that makes use of spatio-temporal model architectures. Soybean yields in the United States were predicted at the county level using a convolutional neural network (CNN) and a long short-term memory network (LSTM) [8]. A CNN-LSTM and a 3D-CNN model were used to classify crop types in Ghana and South Sudan using multi-layer remote sensing time series data frames from [9]The authors of [10] built and trained a bidirectional ConvLSTM to predict crop maps using satellite data from the start of the growing season in Nebraska. Using characteristics like temperature, plantation, rainfall and a certain latitude,[11] created an innovative, intelligent framework based on the clustering kernel methodology to estimate farm yields. The analysis of oil palm plantations used a spatially constrained weighted k-means kernel method. An ensemble of researchers led by [12] hybridized three algorithms (clustering k means, Apriori, and Bayes algorithm) to account for variables such as land area, precipitation, soil type, and other environmental factors, thereby improving the accuracy of yield predictions. It was proposed that an Artificial Neural Network (ANN) and Multiple Linear Regression (MLR) be used together to improve the accuracy with which agricultural output might be predicted [13]. Nevertheless, the input weights converge too quickly in the hybrid approach because they encounter global minima early in the iterative process. A neural collaborative filtering method [14]was introduced to predict the yield performance of parents in plant breeding. The effectiveness of its forecasts can be enhanced by include additional crucial parameters, such as weather components and soil conditions. Deep learning methods [15]were used to forecast winter wheat harvests in China's major wheat-growing areas. Therefore, it is important to exercise caution when using yield de-trending to anticipate crop yields because it might introduce a high degree of uncertainty into the forecast.[6]have enhanced yield estimation using convolutional and recurrent neural networks to better utilize data from across the spectrum. The authors made two key simplifications: they presumed that spectral bands are uncorrelated and that input image pixels are permutation-invariant. We were able to achieve significant dimensionality reduction while still retaining enough information to make use of the image by substituting the original satellite image with a histogram of per-band pixel counts.[16]proposed a parameter-based model for forecasting crop yield. With this procedure, features were used to determine how successful a harvest was. Estimating wheat yields using multiple linear regression, fuzzy logic, or the adaptive Neuro fuzzy inference system were all proposed. During the preliminary processing of the anomalous, inconsistent, database, redundant, and missing values were removed. The method was able to successfully predict wheat yield, but with a rather high mean squared error rate. [17]proposed a technique for categorizing sugarcane harvests using a hybrid approach. In this proposed approach an unique hybrid method for sugarcane yield categorization using the fuzzy cognitive map learning algorithm. The range of soil and weather factors that can now be taken into account by this algorithm was expanded. The classification and inference abilities of this hybrid learning system were evaluated and compared to those of machine learning methods. However, the efficiency of evolutionary computation for classification still required improvement before it could be used in agricultural surveillance. In recent years, researchers have also explored the possibility of using remote sensing data to estimate crop yields. Normalized difference vegetation index (NDVI), surface temperature, rainfall data, and soil moisture are used in a linear regression and a non-linear QuasiNewton multi-variate regression model by[18] to estimate soybean yield in Iowa. [19]use a deep neural network and support vector machine to predict crop yield at the county level in Illinois, utilizing EVI (Enhanced Vegetation Index) data collected from MOD09A1. Regression trees are trained to predict

corn and soybean yields by [20]using NDVI and daytime land surface temperature data (obtained from the Aqua MODIS sensor product MYD11A2).Models based on neural networks have gained popularity for predicting agricultural yields as a result of recent developments in deep learning ([21];[22]). To begin, we said that about half of the recently reviewed works, or 47, made use of neural networks. Nearly as many CNN-based works as RNN-based ones were found. Being inspired by the above researchers the proposed approach uses CNN-BiLSTM-ECA model to increase the accuracy and to reduce the computational time.

III. PROPOSED SYSTEM

Research into estimating crop yields requires a wide range of production parameters and algorithms. Some use algorithms for determining which traits are the most predictive, while others use prediction algorithms. Here you'll find a framework that makes use of Neural Networks to predict agricultural yields with high precision and a short lead time. This proposed approach to start by gathering as much information as possible on the crops as inputs. The Relief approach is then used to pick the attributes. By categorizing important characteristics relevant to a certain real-world scenario, feature selection aids in the generation of reliable outcomes. The LDA method is then used to extract the features. Subsequently, classification is performed using CNN-BiLSTM-ECA.

A. Need For Crop Yeild Prediction:

Because of its significance in national and international economic planning, the prediction of crop output, especially for strategic plants like wheat, corn, and rice, has always been a fascinating research subject for agro meteorologists. There are several factors that influence crop yield in dry farming, including the genetics of the cultivator, the edaphic conditions, the impact of pests and pathogens, the quality of management and control exercised during the course of the growing season, and the weather. Consequently, it is not out of the question to gain relations or systems that can make more precise predictions utilizing meteorological data[21]. The many yield prediction models available today can be roughly divided into two categories: a) statistical models and b) crop simulation models (e.g., CERES). In this proposed approach to CNN-BiLSTM-ECA was used in an attempt to create a model that could predict future crop yields. Long-term and short-term estimates of crop production are possible, and a CNN-BiLSTM-ECA model can be obtained for each region if a network is designed that correctly learns the relationships between effective climatic parameters and crop yield. Also, the most influential elements on crop productivity can be identified with the use of CNN-BiLSTM-ECA. As a result, it can exclude the effects of those elements whose measurements provide significant challenges and high costs. Here, people focus exclusively on how the weather plays a role in predicting harvests.

B. Preprocessing

To apply models to this dataset, you'll need to figure out how to deal with the missing data. To identify and get rid of any null values, reverse filling is utilized as a preprocessing approach. After the missing data has been accounted for, it can be used in the model to make predictions about crop yield[13]. The data set is preprocessed so that missing values may be filled in and anomalies can be removed. The outcome was only as good as the input data allowed it to be. Using missing value treatment, it's scrubbed the data for errors. All of the attributes in this data set are quantified individually. The dataset was rescaled with the equation in order to achieve precise forecasting.

$$\mathrm{Z}' = \mathrm{Z} - -\frac{\min(\mathrm{Z})}{\max(\mathrm{Z})} - -\min(\mathrm{Z}) \quad (1)$$

Where Z is the original value, Z' is the new value, $min(Z)$ is the lowest possible value for Z, and $max(Z)$ is the highest possible value for X.

C. Feature Extraction

Specifically designed to aid with categorical decision-making issues, relief is an instance-based learning method. Filtering is an approach of discovering relationships between features. Nearest neighbors are used to account for the relationships between variables in feature statistics. Nevertheless, this method does not take into consideration data with missing values or numerous categories. Attribute estimation is achieved with great accuracy using RA. It picks and chooses which features are worth focusing on. It finds the nearest neighbor by picking a case at random from the database[23]. Each attribute's relevance score is updated based on a comparison between the sampled instance and its nearest neighbors attribute values. RELIEF looks for two nearest neighbors for a given instance, one from the same class as the instance (nearest hit) and one from a different class (nearest miss). The estimate $V(C)$ of attribute C provided by RELIEF is a rough approximation of the following probability distancing:

$$\begin{aligned} &V(C) \\ &= Q\left(\frac{Diff\ value\ of\ C}{nearest\ instance\ from\ different\ class}\right) \\ &- Q\left(\frac{Diff\ value\ of\ C}{nearest\ instance\ from\ same\ class}\right) \end{aligned} \quad (2)$$

A good attribute, the thinking goes, will be able to tell one class of instances apart from another, while giving all instances of the same class the same value.

D. Feature Selection

Reduce the size of your data matrix via linear discriminant analysis (LDA). It is also worth noting that PCA and LDA are linear transformation methods. PCA is an unsupervised method, while LDA requires human oversight. Aiming to optimize class reparability, LDA seeks a feature subspace in addition to finding the directions of highest variance, like in PCA. Over fitting is prevented and computational costs are reduced when class reparability is prioritized. For future data, the LDA method is used to classify them into one of the previously identified groups by determining which functions are most effective in discriminating between sets of observations from two or more categories. Let's pretend p variables are available and you need to sort k data into those categories. The method entails locating linear or quadratic functions with coefficients chosen to maximize the difference in variance between groups as compared to that of the groups themselves. It is possible to obtain at most k-1 less than p discriminant functions. Discriminant scores, which are calculated using these functions, are then used to categorize the observations into distinct categories.

E. Training the Model:

This proposed approach a new crop yield prediction network model called CNN-BiLSTM-ECA, which combines CNN and a BiLSTM network with a lightweight ECA attention module to extract features quickly and increase prediction accuracy. By making use of the data at hand, our proposed model can automatically train and extract local features and long memory features for crop prediction. To begin, the raw agricultural yield data is fed into a CNN model to be transformed into deep feature vectors. Afterwards, the deep feature vectors are used to generate new crop yield data, which is fed into the BiLSTM model, which is trained to extract temporal features. In addition, a new attention mechanism called ECA is introduced to help with feature extraction. In the end, the prediction job is done using a dense model with multiple fully linked layers. Figure 1 depicts the overall model architecture for a network.

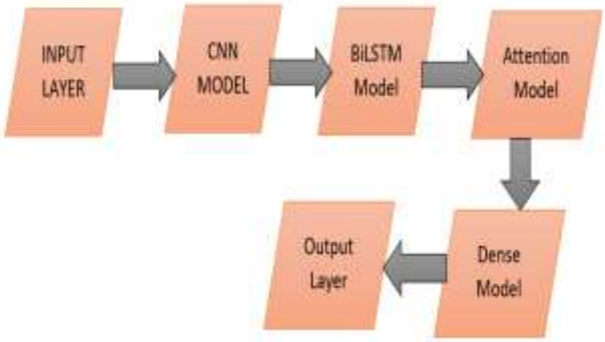

Fig. 1. Model Architecture

1) Convolutional Neural Network:

In this proposed, it employs a CNN (Convolutional Neural Network) to effectively extract data features. CNN is a local connection between neurons, which decreases the number of parameters between the connection layers compared to the standard neural network architecture[24]. In other words, it includes some of the links between the CNN's n+1 and nth layers.

2) Biderctional-LSTM

By serving as a forward and a backward LSTM network for each training sequence, the BiLSTM network is used to construct a more precise prediction model. This proposed approach may ensure that each sequence point is well-informed by linking two LSTM networks to the same output layer.

3) ECA Channel Attention

The performance of Deep Convolutional Neural Networks can be greatly enhanced by employing the Channel Attention (CA) mechanism (DCNNs). Most current approaches, however, are focused on developing ever-more-complicated attention modules in the pursuit of higher performance, which in turn raises the model's complexity and computing weight. Effective Channel Attention (ECA) is a lightweight and low-complexity module designed to prevent model over fitting and reduce computational overhead. Not only can ECA create weights for each individual channel, but it also has the potential to reveal relationships between channels. The time series data will have bigger weights allocated to the features that are more important, and smaller weights assigned to the features that are less important. In this way, ECA increases the network's responsiveness to the most salient features by zeroing in on the most relevant data.

World Average Pooling for Channels is a first for ECA (GAP). To record the local cross channel interactions, ECA uses each channel and the i channels immediately surrounding it. Fast 1D convolution is used by ECA to generate channel weights, as shown below:

$$V = \beta\big(CID_i(z)\big) \tag{3}$$

Where 1D convolution (C1D) is represented by D and the kernel size of 1D convolution z is denoted by i. ECA uses a channel dimension adaptively mapping approach to find the value of i so that it doesn't have to be manually adjusted. The following expression defines the relationship between the kernel size i of 1D convolution and the channel dimension D.

$$D = \varphi(i) = 2^{(\beta * i - c)} \tag{4}$$

Hence, the kernel size i can be computed adaptively, given the channel diameter D, by

$$i = \varphi(D) = \left(\frac{(\log_2 D)}{\beta} + \frac{e}{\beta}\right)_{odd} \tag{5}$$

To the nearest odd number, where $|\,|_{odd}$. In this work, the values 2 and 1 are used for the β and e parameters. The range of interaction possible in a high-dimensional channel due to nonlinear mapping is clearly greater than that of a low-dimensional channel.

4) Dense Model:

First, dense models map the input space to the output space utilizing the entire connection layer in order to retrieve the correlation between the properties that were modified by the nonlinear mapping. The suggested model uses a network architecture consisting of three independent but interconnected layers to solve the nonlinear problem and make reliable forecasts.

IV. RESULT AND DISCUSSION

Research into predicting agricultural yields requires multiple production contexts and approaches. Some algorithms are used to create predictions, while others are used to identify the traits that are most predictive. In this section, they outline a methodology for applying machine learning to reliably forecast agricultural output in the early stages of the production cycle. The supplied data set requires preprocessing before it can be used. The Relief approach is then used to pick the attributes. Selecting features that are most relevant to a given scenario in the real world allows for more solid inferences to be made. The LDA method is then used to extract features. After that, categorization is accomplished via CNN-BiLSTM-ECA.

The work employs neural network models such as CNN, BiLSTM to estimate crop yield based on the appropriate crop factors. Root Mean Square Error (RMSE) and Loss were used to assess the neural network model's efficacy. The model is executed for 60 EPOC, and the resulting evaluation value is shown in Table 1. The CNN-BiLSTM-ECA model outperforms well on comparing to CNN and BiLSTM, as shown by the results.

TABLE I. EVALUATION OF THE MODELS

Models	Number of Epoch	RMSE	LOSS
CNN	60	0.245	0.2153
BiLSTM	60	0.139	0.1156
CNN-BiLSTM	60	0.00010	0.0123

The Root Mean Square Error was used to compare the various neural network models. You can see the outcomes for the CNN, BiLSTM, and CNN-BiLSTM models in figure 2.

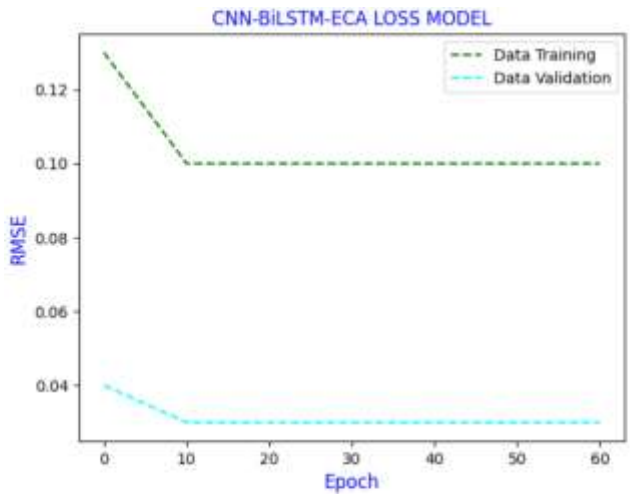

Fig. 2. RMSE Evaluation of CNN-BiLSTM-ECA Model

Using loss of error as a metric, the proposed approach compares the CNN, BiLSTM, and CNN-BiLSTM-ECA. Predicting agricultural yields with CNN-BiLSTM-ECA is more accurate while still being relatively error-free. Because of this, farmers would be able to choose the best crop for their needs.

TABLE II. MODEL COMPARISION

Models	Accuracy	Precision	Recall
CNN	94.64	91.86	89.72
BiLSTM	95.83	92.76	90.32
CNN-BiLSTM	98.47	96.54	94.29

The three models (CNN, BiLSTM, and CNN-BiLSTM-ECA) presented in Table II are the result of a model selection approach. The experimental results show that the CNN-BiLSTM-ECA algorithm model is significantly superior to the other three models.

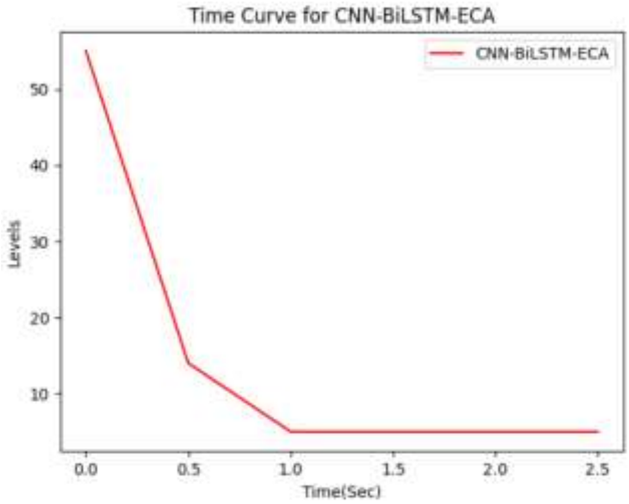

Fig. 3. Time Curve of CNN-BiLSTM-ECA Model

Figure 3 shows the amount of time it took for CNN-BiLSTM-ECA to compute. The x-axis of these graphs depicts time in seconds, while the y-axis shows execution depth. For the standard CNN-BiLSTM-ECA dataset, see Fig. 3. Experiments on the time curve of CNN-BiLSTM-ECA showed no difference in the performance. The early stages of the CNN-BiLSTM-ECA hybrid model were smoother and more refined than those of either CNN or BiLSTM alone. CNN-BiLSTM-ECA model achieved this smoothness by modifying the weights initialization procedure.

V. CONCLUSION:

The agricultural economy of the developing countries and Africa is particularly vulnerable to climate and other environmental changes. High costs of transactions, adverse selection, asymmetric information, poor distribution, and other problems make traditional insurance for financial risk management in poorer nations unfeasible. The agricultural system is notoriously difficult to understand because of the massive amounts of data it must process. Producers, consultants, and agricultural groups have all taken an interest in the possibility of accurately predicting crop yields. The preprocessing method can be used to remove the blank values from the input image. The characteristics are then selected using the Relief technique. A linear discriminant analysis strategy is utilized to extract features. Finally, the CNN-BiLSTM-ECA model is offered for training purposes; this model includes a CNN, a Bidirectional Long Short-Term Memory network, and an Attention Mechanism (AM). To minimize the complexity of the model, it present a method for automatically training and extracting local features and long memory features from the time series. The proposed approach outperforms well when compared to other models such as CNN and BiLSTM which produces an accuracy of about 98.5%.

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