Enhancing Crop Yield Prediction Using Deep Convolutional Neural Networks: A Data-Driven Approach for Agricultural Optimization

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Abstract. Farmers have become more and more interested in data-driven methods over the past few years because they help them to see the future problems. In smart farming, they are often used to predict what kinds of plants will grow. The study's goal was to create a useful hybrid deep learning model that could predict how much rice crops would yield by mixing a regression model with a deep learning classification model. It was possible because the layers were shared. Stats can be used to do three different types of tests. These are the Pearson correlation coefficients (PCC), the Shapley additive reasons (SHAP), and the repeated feature elimination with cross-validation (RFECV). The study's goal is to find the most important parts of the forecast goal so that the model can be trained more quickly. Putting together all the different parts of data that were sent is the first thing that needs to be done to get the data ready. The features are then turned into a three-dimensional grid. You can figure out how much rice was grown if the R-squared value is 0.64 and the RMSE value is 344.56. AI networks (RMSE = 550.03, R-squared = 0.09) and multi-parametric deep neural networks (MDNNs) (RMSE = 370.80, R-squared = 0.59) are not as good as the model that was suggested. The F1 test gave it a score of 94%. It's now much better at telling the difference between high yield and low yield.

Keywords*:* Preprocessing, Overall Design, Proposed Model, deep learning, multitask learning.

1 Introduction

A lot of people eat rice, which is a big grain. Every farmer in the world cares about it. When farms grow too much rice, it can hurt food safety, the economy, and their long-term ability to stay in business [1]. This is because many people eat rice every day. Rice makes a lot of important things possible on farms all over the world. One clear reason is that it feeds a lot of people, mostly in Asia, where most rice is grown and eaten. Many folks eat this wheat grain every day since it gives them the carbs, food, and power they need. A lot of people eat rice, and it helps companies grow. Many people need to grow, cook, and move this food for a job. A lot of places need to buy and sell rice to get what they need and stay in business. That is people

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around the world trade rice. So that rice can be grown, the land is changed, the water sources are changed, and the land itself is changed [2]. They have a long way to go before they can guess how much rice will grow. They know how much food will grow so that they can choose the right plants, feed and water them, and gather them.

So, we use the ground to find the amount of water, biomass, and leaf area index (LAI) of the plant. This helps us picture what rice fields look like when the plants grow at different speeds or when the weather is different. The land will be better off, and you can grow more food. A lot of people around the world grow rice to make money and eat [3]. What will happen when people figure out how to grow rice best with the right tools and weather? People will be able to make more money, grow more rice, and throw away less trash. To do this, you need to learn how to grow the fastest.

A lot of people around the world eat rice every day. More than 21% of people in the world get most of their energy from food. This is very important to keep everyone healthy and fed. Think about how much rice will be grown to help the farm business plan and figure out what to do. These steps will make sure that there is always food, that prices don't change [4], and that resources are used in the best way possible. If they care, they can find out ahead of time what people want and how the market will change. They check to see if everything is okay and are ready to act right away if something changes or comes up. The area, the drugs used, and the weather have all changed. A lot of the ways that rice is grown have also changed. Do these things to see what happens. Quantitative trait loci (QTL) were linked to how plants flower and grow in a study [5].

A lot of people around the world eat rice every day. More than 21% of people around the world get most of their energy from food. To keep everyone fit and fed, this is very important. To help the farm business plan and figure out what to do, think about how much rice will be grown. These steps will make sure there is food all the time, prices don't change, and resources are used in the best way possible. They can find out what people want and how the market will change ahead of time if they care. They make sure everything is okay and are ready to act right away if something comes up or changes. Both the drugs that were used and the weather in the area have changed [6].

These things have to do with very small quantum computers. This kind of mixed model is what this study is all about. We want to make a tool that will help farmers all over the world plan their farms and guess what will happen next [7].

The most important things that this study adds are these:

- You can now guess how much rice will be grown with a new mixed quantum deep learning model.
- Show proof of how quantum feature processing could help people make better predictions and better use of data.
- To get the most out of both ensemble methods and deep learning, Bi-LSTM and XGBoost should be used together in a model.

2 Literature Review

Food growth predictions use a lot of machine learning to help farmers make as much money as possible by making the crop better. In general, farming is getting better, which is good for business. You can find out a lot about this subject. This study shows that machine learning can be used to guess how much palm oil will be made. When they put the linked works next to each other, they thought about the good, bad [8] and limited points of each method. With the help of machine learning, it was possible to guess how much palm oil would be made. Because of what was written and talked about before, this was done. The people who wrote both were better able to guess what plants would grow and how much they would earn. The dirt tells plants how much food to grow [9]. It was checked for temperature, NPK levels, humidity, PH value, and how wet it was. Three different types of machine learning systems can go up against each other. Naïve Bayes, Random Forest, and Logistic Regression are a few of these. They also thought about how true each side was to help them decide [10].

A machine that helps make food tries to keep track of the plants that are grown. To begin, it should help the farmer pick out the best plants for their area. After that, it should tell them how to get the land ready to plant. Third, it needs to teach them how to sell their things in the best way. There are several ways to do it, such as Choice Regression, Voting Regression, or Random Forest Regression. You could also use information about speed, weather, and dirt. This is good for businesses all over the country. It's hard to find some things in this world. ML and cell phone pictures will be used in this project to keep track of how little parsley and cotton plants grow. To lead machine learning, they learned how to use C-NN, K-NN, GNB, LR, and Random Forest. They knew what would happen after seeing this. Please find the best way to use machine learning to guess when plants will grow and keep an eye on them. This could make smart farming better. This is very true for things like cotton and chilli. The Indian Tamil Nadu Agricultural University (TNAU) looked at the dirt that year. There were 32 of them.

The Root Mean Square Error was 13%. You can guess how much food Mars will grow. That job was done by a group called the Mutual Research Center [11]. DL learned about plants quickly and guessed how they would grow [12]. They guessed how many soybeans would be grown before the field was even tilled by using DL algorithms and data from a long way away . People did better things when they knew more about the land and the area around it [13]. A study that has already been made public says that the DT algorithm-based material needs to fit the data better, which leads to wrong results. Here is a list of some of the most troublesome works:

- How much food will a farm grow? Read the study that goes with this one. The method has more signs.
- You need to use this method to plan all of your farming jobs better [14].
- The weather should be part of the study that goes with the answer so that the number is more accurate.
- To get a more accurate estimate, the linked study needs to add more crop-related factors to the method that was suggested [15].
- The work that goes with this one needs to find better ways to guess what will grow.
- The study won't be as good as it would have been if the model used had been correct.

3 Methodology

The first step in this plan is to get the data ready based on the attributes that were selected. Next, an MKCNN and Bi-LSTM mixed model is being made to guess how much food will be made.

3.1 Preprocessing

Before it could be used, this mixed model had to be cleaned up and put back together. Because of this, the most important improvement to each trait in this study comes from the following:

$$\hat{x}_i = \frac{x_i - x_i^{min}}{x_i^{max} - x_i^{min}} \tag{1}$$

Equation 1 shows, xi the average value is xi, and the lowest and highest values of feature i are $xmini$ and $xmbxi$. It was thought that all of the trait numbers would be in the range. To try to figure out what the goal was, different size factors were used. That is, the information needs to be made the same. When all the plots are put together, Fig.1 shows what the three-dimensional grid looks like.

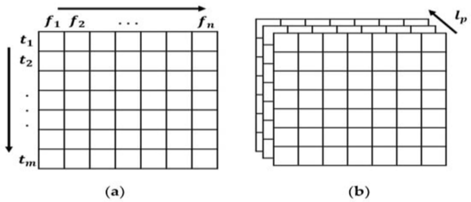

Fig. 1. Data reconstruction for an agricultural unit and the whole farmland.

For the Bi-LSTM, the time stamps $t1$, $t2$, tm are split up into different parts. Every part has all of the remote sensing traits $f1$, $f2$, $f\boldsymbol{T}$. Due to a mistake, each date comes after the last one.

3.2 Proposed Model

Two different kinds of deep learning models are put together in the mixed model that was suggested. You can now see the info in both stream mode and block mode. It works better now, and you can learn more. Fig.2 shows the suggested model form from a bigger picture point of view. The MKCNNs were made with these blocks, which are called MS-Blocks.

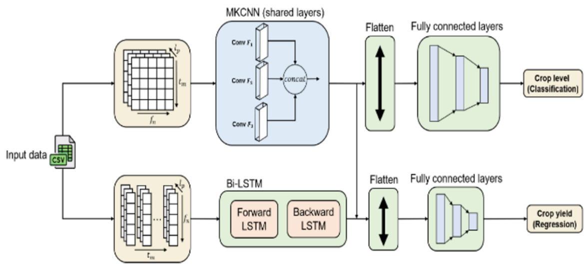

Fig. 2. A hybrid model using MKCNN and Bi-LSTM architecture is suggested.

Bi-LSTM and MKCNNs made up most of it. This is the first thing that needs to be done. An MKCNN needs a grid with three dimensions. The very first thing that needs to be done is called "preprocessing." As part of the regression work, a rough idea of the crop yield is given at the end. This is a deep learning model that can work with grid-based data, like pictures or rows of data that have more than one column. CNN is a big part of MKCNNs. They use information that is set up in a grid to do their jobs. Another part is the pads. Another layer is fully linked, and there is also an activation function and a convolution layer. Fig.3 shows a picture of the multi-kernel block.

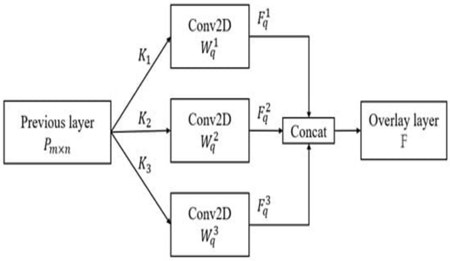

Fig. 3. Multi-kernel block architecture.

The more convolutional things we use shouldn't make the feature maps less real. This will give us three types of states, which are shown by 1, 2, and 3. Make a flat grid by putting these shapes together. This is the last step. This is a more in-depth look at the forget gate, which chooses whether to delete data or not given a stream of data $x1$, $x2$,..., xM times, with output $yt-1$ and secret state $ht-1$ Equation (2).

$$f_t = \sigma(W_f[h_{t-1} \cdot x_t] + bias_f) \tag{2}$$

The letter **p** stands for the sigmoid function, and the letter M represents the forget gate's weight matrix. The last hidden state ($\hbar-1$) is used to get the value of the input at the time step. After that, the gate will say "yes" or "no." Equation (3) shows that this is right. Step 4 and Step 5 are the same. They both talk about the secret state ($\hbar$) and output state (***T***) of the LSTM. Remember that the time step cell could be seen as a middle variable.

$$i_t = (W_f[h_{t-1} \cdot x_t] + bias_f) \tag{3}$$

$$h_t = o_t \cdot tanh(C_t) \tag{4}$$

A simple RNN takes longer to find long-term trends than an LSTM. LSTM, on the other hand, can only use what it already knows. The loss function can be explained in the following ways: Equation (4,5)

$$\mathbb{L} = \sum_{i=1}^{N} w_i \mathcal{L}(\theta_i, t_i) \tag{5}$$

$\mathscr{L}$ shows the loss function in ti, and the fraction of loss in $\mathscr{L}$ is shown by ei.

4 Experimental Analysis Of Rice Yield Prediction Based On Deed Learning

4.1 Design in General

Data for this study came from about 207 plots of rice fields. Twenty of the same type of rice trees were planted in each plot, but the rice in each field was different. These pictures show a group of rice ears, a grain being looked at for seeds, and a single rice ear. They are all from different rice fields. After that, this is used to make the regression equation that connects the different parts of the plot to the whole. You have to guess how much rice a plot will grow next. You need to look at the relationship between the dependent variables (the plot results) and the independent variables (the picture parts) in order to make a hard regression equation. To use this method, you need to look at the different things. It has two parts: simple regression and multivariate regression.

4.2 The Test of Normality of the Plot's Whole Output

A lot of rice was grown and saved, as shown in Fig.4. This is what is being looked at. A Q-Q chart and a histogram are used to do this.

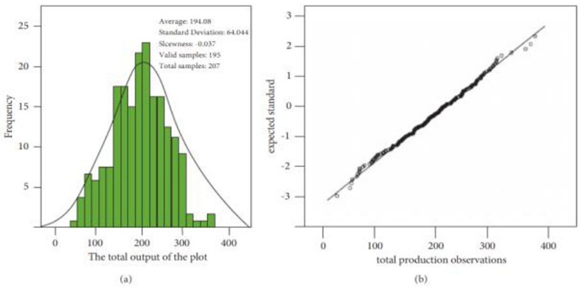

Fig. 4. Histogram and Q-Q diagram of total production in the field.

It's shown in Fig.4, which is a list of facts. The histogram is off by -0.037, which is very close to 0. In other words, the dependent measure has a range that is more even. By making a Q-Q map of the variable, we can see that it has a normal distribution. It's even more clear now. The curve points are farther apart when they are close to a straight line than when they are far away. You can use two different SPSS tests to check if the dependent factors are spread out just right.

When you grow rice, you need to know how many ears are in a certain area, how fast the seeds grow, and how many grains are in each ear. When you want to talk about going back, you can use these words. You can use this to make a regression model that shows how much rice grows in each plot. After modelling four things that affect rice growth, this choice was made. You can get a good idea of how many are in a certain place by looking at the scaled part of the ears from different angles. A lot of people use the goodness-of-fit (R2) measure. Use this method and look at the regression data to find out Equation (2).

$$R^2 = 1 - \frac{SSE}{SST} \tag{6}$$

It's also called the 2L blank form. SSE stands for the sum of the squares of the sample residuals. But SST, which stands for "sum of all squares of samples," is just that: a sum of all squares of Equations (8) and (7) can help you find SSE and SST.

$$SSE = \sum_{i=1}^{N}(y_{i-}y_i^{*}) \tag{7}$$

$$SST = \sum_{i=1}^{N}(y_i - \overline{y} \tag{8}$$

To find the mean of a group of real numbers, you can use math. People thought they knew what the fifth example should have been, but you showed them. The R2 can change in a lot of different ways between regression fits. When there is more of something, it changes more. When you look at the R2 of the regression model, think about how many different traits there are. That's the reason. After seeing all the possible outcomes for each factor in SPSS, you can talk about how well the model fits. This is done with the changed goodness-of-fit, which is also called changed R2. To describe it, use this sentence Equation (9), which shows what it means for R2 to have changed:

$$AdjustedR^2 = 1 - \frac{N-1}{N-M-1}(1 - R^2) \tag{9}$$

There are a lot of things there because the degree of freedom of each factor is written as M. N. M. It can also be written as the variety of things that make up the group.

- **How to Predict Yield Based on the Size of the Rice Ear** A scatter map connects the plot rice yield to the area that changes in the Fig.5 plot rice spike picture. The R2 number for the match between TPCA and FPRY is 0.2883. The R2 number for the goodness-of-fit between OPCA and FPRY might be around 0.412. The plot's rice ear area has changed, as shown in this shot Table 1.

Table 1. Relationship between rice earimage and rice plot yield

Attribute	**Top-view (Plot a)**	**Overlooking (Plot b)**	**Which is Better?**
Regression Equation	$Y = 0.1661x + 118.18$	$Y = 0.0873x + 83.264$	—
R^2 Value	0.2883	0.4112	Overlooking (higher explanatory power)
Slope	0.1661	0.0873	Top-view (steeper increase per pixel²)
Yield Prediction Strength	Weak correlation	Moderate correlation	Overlooking
Practical Implication	Captures ear area but less predictive	Captures ear area with better yield estimation	Overlooking view is more reliable

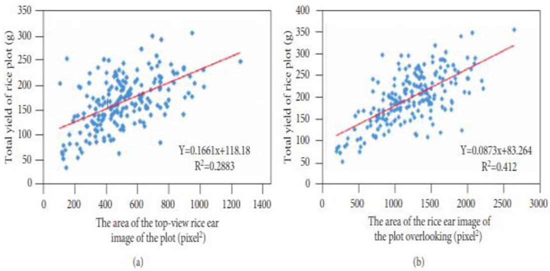

Fig. 5. Correlation analysis between the TPCA, OPCA, and FPRY.

5 Conclusion

Our second model fits well because its r2 value is 0.413. After seeing the data, everyone decided that FPRY would work better if it had single seed test features. It's not a surprise that when things get better, and more people live, they want more food. Farmers have always been most interested in rice, which is their main crop. Guessing how much rice will be grown has always been fun and useful. When there is only one random variable, the link between OPCA and the rice plot's total result is stronger than when there are two. The way the study is set up makes this clear. You need to cut the rice ears the right way if you want to know how much you will get. The image that was taken from the stand-by view also helps figure out the return. You can use the rate at which seeds grow and the weight of 1,000 grains for each plant to get the rate and weight for the whole area.

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