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Agricultural Cultivation Cost Prediction Using Neural Networks and Feature Importance Analysis

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Abstract

Agriculture is one of the most important sectors integral to human civilization, and technological adaptation is necessary to maintain its quality. This research aims to achieve high productivity in the agricultural sector by using neural networks or Deep Learning methods to predict the cost of agricultural cultivation, as well as identifying significant factors that affect the profitability of potato commodities with Feature Importance analysis. The research process includes the stages of Data Preparation, Data Understanding, Split Data Training, Classification Model Building, Training, and Evaluation. Evaluation techniques such as MAE, MSE, and R² were used to assess the effectiveness of the model. The results showed that the prediction model almost achieved optimal performance, with the Cost of Cultivation C2 factor having the greatest influence in understanding the data and guiding improvements to the significant factors affecting cultivation cost prediction. The main contribution of this research is the application of optimal Deep Learning methods to predict the cost of cultivation as well as identify the main components that impact the profitability of potato farming in India.

Keywords: *artificial intelligence; cultivation cost; deep learning; mean absolute error; mean squared error; R-squared*

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1. Introduction

One of the industries that is very important to a country's economy is agriculture. Agriculture involves activities related to producing commodities such as food crops, horticulture, plantations, or livestock. It encompasses all forms of resource management activities, including flora and fauna, with the help of technology, capital in the form of money, labor, and business management places managed by companies or the government [1].

Which also makes a significant contribution to the country. A wide range of food products and raw materials are produced by agriculture. Agriculture is the use of biological resources for human needs, including environmental management and the production of food, industrial raw materials, or energy sources [2].

Because most of its people are farmers and agricultural goods are used on a daily basis, Southeast Asia stands out among other agriculturally advanced regions. Because all of the countries in Southeast Asia are equatorial, the region is strategically located. Its tropical environment is complemented by geographical features that are favorable to agriculture, such as plenty of sunshine, rainfall, and certain types of soil. The region's fertility and wealth of natural resources have an impact on how local community activities are organized. The agricultural sector in each country results in various farming or agricultural activities. The science of farm management is the study of how farmers select, organize, and coordinate the use of production components as effectively and efficiently as possible to maximize their farm income [3] Cultivation costs are used to determine the expenses incurred for various inputs during production and the profitability of production in the study area [4].

The agriculture sector in India faces major challenges related to low-cost efficiency, which has a significant impact on the welfare of farmers and their profitability. Most crops in India do not generate sufficient profits, with some even incurring losses. This is due to rising cultivation costs, declining yield values, sub-optimal crop rotation techniques, excessive pesticide use, low-

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quality seeds, and inadequate marketing systems. In addition, significant post-harvest losses further aggravate the situation and hamper farmers' welfare.

In the face of this problem, innovative solutions are needed that can help farmers optimize costs and improve efficiency. Machine learning and deep learning technologies offer new approaches in creating integrated smart farming solutions. By leveraging these technologies, farmers can estimate the total cost of cultivation, optimize resource use, and maximize yields at a lower cost. In addition, learning technologies can assist in scheduling farm tasks more efficiently, thereby increasing production effectiveness. This research aims to explore how learning technologies can be used to improve cost efficiency in the Indian agricultural sector, providing a more sustainable and profitable solution for farmers.

Estimating the entire cost of cultivation is crucial to solving these issues since it determines how much money can be made from influencing elements like labor efficiency, land area, and production levels. Farmers' income is also subject to fluctuations as a result of frequently fluctuating and unpredictable factors like price and production.

Facing global issues such as shrinking agricultural land, climate change, and protecting crops from unfavorable conditions, cultivation is an effective way to increase crop yields. Farm culture can significantly increase productivity through the calculation of cultivation costs and can be offset by better yields and higher quality products, especially for high-value crops [5].

Technology is now a necessary component of modern living and is deeply ingrained in both human life and agricultural operations, which helps to handle these difficulties in agriculture.

According to previous research, it has been concluded that agriculture in India faces significant challenges [6], the most prominent being low profitability. The low profitability is primarily due to the majority of crop yields not generating sufficient profit for farmers, with some even resulting in losses. This situation is caused by the declining value of crops and the rising costs of cultivation.

India's agriculture industry has a number of difficulties that have an impact on productivity and efficiency. Insufficient crop rotation techniques, subpar seed, excessive pesticide use, changing climate [7], and inadequate marketing lead to decreased yield and elevated expenses for agricultural producers. Moreover, smallholder farmers and the agricultural sector as a whole suffer enormous losses due to post-harvest losses, which are estimated to be between 10 and 40 percent. Therefore, to increase farmers' efficiency and welfare, efforts are needed to reduce post-harvest losses and encourage more sustainable and creative agricultural practices.

For computer vision tasks in agriculture, these deep learning models are often customized for agricultural tasks. These models are frequently tailored for agricultural tasks utilizing model weights that were initially learned on broader datasets, which can enhance model performance and data efficiency in an agricultural such as disease detection, soil monitoring, and also crop yield estimation [8].

Previous studies indicate that by utilizing machine learning and deep learning techniques, smart agriculture can assist in the effective cultivation of crops and obtain high yields at cheap prices. It also helps in estimating cultivation's total cost. This makes it easier to schedule tasks before they are needed, which results in integrated agricultural solutions [9].

Nevertheless, the characteristic of feature importance has not yet been included in this study; writers will carry out further research on that topic in this debate. In order to prevent any decrease in the value of cultivation costs in the components that need to be examined, the research aims to anticipate agricultural cultivation costs in order to generate the optimal model. It also seeks to identify significant components that were taken into account in predicting these cultivation costs. The purpose of this research is to address the difficulties associated with using technology, particularly with artificial intelligence (AI), or as some refer to it, the technology that is often employed in today's world. But as Figure 1 illustrates, AI itself has deeper levels or components.

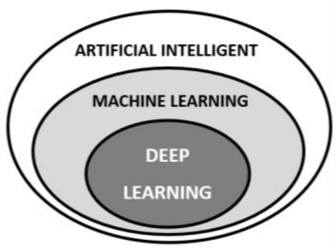

Figure 1. Components in AI, Machine Learning, and Deep Learning

Figure 1 shows Artificial Intelligence has deep components, with the first layer of Artificial Intelligence being machine learning. The machine learning subfield is about creating systems that can learn 'autonomously' and without continuous human programming. Machine Learning (ML), a subfield of artificial intelligence, focuses on learning from data [10].

Using data to learn is the aim of machine learning, also known as statistical learning or predictive analytics. This area of study combines statistics, artificial intelligence, and computer science [11].

The more sophisticated level of machine learning is called deep learning which was shown in Figure 2. It is a branch of artificial intelligence that trains computer models to comprehend and evaluate highly abstract material in order to make judgments on their own. It entails creating artificial neural network designs and algorithms that can comprehend complicated, unstructured data and identify patterns and classifications, particularly when it comes to interpreting text, images, and sounds without the need for human participation.

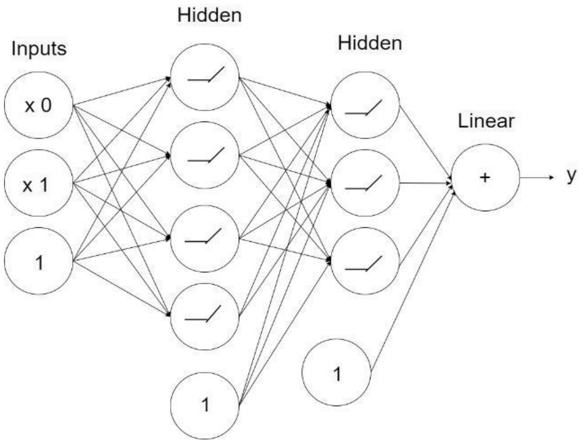

Figure 2. Layer stack specifications in Deep Learning

Deep Learning is a branch of machine learning that builds high-level abstractions from data by layering non-linear transformation algorithms. Applications such as text classification, audio recognition, image identification, and unsupervised and semi-supervised learning can all benefit from deep learning's potent reinforcement learning capabilities [9]. Deep Learning, a branch of artificial intelligence, involves simulating very large neural networks capable of making accurate assessments based on inputs. Large datasets and complex data make deep learning ideal for such situations [12].

Deep Learning is a type of feature-based learning where the number and shape of hierarchical features can be scaled to fit specific examples being handled. Therefore, Deep Learning algorithms are capable of precisely and automatically extracting features from unprocessed input. This is made feasible by the extraction procedure, which uses an exploitation structure that hides the exploited features from view [10].

This research will focus on predicting agricultural cultivation costs, which include operational costs, material costs, and other costs involved in plant production. Labor, machinery, and livestock costs are determined as part of operational costs using the applicable rates for a specific period in the study area [13].

2. Research Methods

Figure 3 shows the proposed method which contains nine stages including Data Preparation, Data Understanding, Data Transformation, Split Data Training and Testing, Classification Model Building, Optimization Hyperparameter, Determine Best Model, Training, and Evaluation.

The purpose of this study is to concentrate on a case study from the Directorate of Economics and Statistics, Department of Agriculture and Farmers Welfare, Ministry of Agriculture and Farmers Welfare, Government of India, by sampling agricultural data or datasets, the variables in this study are cities in India, including Assam, Bihar, Gujarat, Himachal Pradesh, Uttar Pradesh, and West Bengal. One of the samples taken is potato cultivation from the dataset shown in Table 1, covering 2018 to 2022. The selection of this potato dataset is because, in a pure dataset, there are many agricultural commodities, but researchers took the potato dataset because, in some potato commodities, there are several countries that are not fully incorporated.

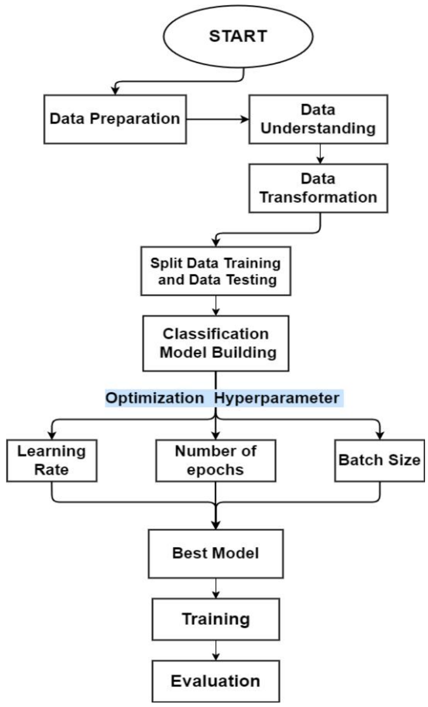

Figure 3. Proposed Deep Learning Scheme Stages

Table 1: Potato cultivation dataset sample for 2018-2019 from the Directorate of Economics and Statistics, Department of Agriculture and Farmers Welfare, Ministry of Agriculture and Farmers Welfare, Government of India.

Items	Year	Assam	Bihar
Cost of Cultivation (Rs./Hectare) A1	2018	60237.33	51195.4
Cost of Cultivation (Rs./Hectare) A2	2018	60254.38	51195.4
Cost of Cultivation (Rs./Hectare) B1	2018	61527.19	52359.03
Cost of Cultivation (Rs./Hectare) B2	2018	81657.92	75055.82
Cost of Cultivation (Rs./Hectare) C1	2018	85781.37	62587.9
Cost of Cultivation (Rs./Hectare) C2	2018	105912.11	85284.7
Cost of Cultivation (Rs./Hectare) C2 Revised	2018	105912.11	85284.7

The variables chosen for this study and added to the model for a detailed examination are called input or x variables. These variables supply the necessary raw data between the many parameters in this study, making them essential components in the modeling and analysis process. The following list of variables has been identified and will be used in this investigation; these variables are significant in deciding the study's outcome:

Cost A1 consists of the value of hired human labour, the Value of hired and owned bullock labour, the Value of hired and owned machine labour, the Value of seed, including both self-sown and purchased seeds, the Value of manures, including both owned and purchased and fertilizers, Depreciation, Irrigation charges, Land revenue, Interest in working capital, Miscellaneous expenses.

Cost A2: Cost A1 + Rent paid for leased-in land

Cost B1: Cost A1 + Interest on fixed capital, excluding land

Cost B2: Cost B1 + Rental value of owned land + Rent for leased-in land

Cost C1: Cost B1 + Imputed value of family labor

Cost C2: Cost B2 + Imputed value of family labor

Cost C3: Cost C2 + 10% of Cost C2, as Management Cost.

The goal of the analytical model is to forecast the entire cost of crop cultivation, the model's primary output is the column labeled "total cost." The column, which serves as the study's target or y-variable, will be thoroughly examined. This y-variable is anticipated to yield useful data that enables estimation and comprehension of the different aspects influencing the overall cost of crop production, allowing for the application of that knowledge to more effective and well-informed decision-making.

Performing data understanding, and analyzing data to understand the characteristics, distribution and features present in the dataset. used to ensure the model built can learn effectively and provide accurate results. In this case, data understanding combines data from the range of 2018-2022.

The data transformation stage is a process to ensure that the data format is optimized and ready to be used in training Deep Learning models. This process includes rearranging the data structure to make it more organized and suitable for the needs of the model. Features that are relevant and related to the analysis will also be adjusted or changed, with the aim of improving the model's ability to recognize important characteristics of the data used, so that the training process can run more effectively and produce more optimal performance.

2.4 Split Data Training and Data Testing

Grid search which is shown in illustration in Figure 4 is a method used in hyperparameter optimization for machine learning models that involves systematically testing combinations of various parameter values. Essentially, grid search forms a 'grid' of possible parameter values and then performs training and evaluation of the model for each combination of parameter values. This stage is a model development process to ensure that the model built can generalize well, in this problem the author separates the dataset into two parts, namely training data (training data) and testing data (testing data). By taking 80% of the data for training and 20% of the data for testing. The 80% data model is used for the learning model in Deep Learning, and 20% of the data for testing is used to ascertain whether the predictions made are correct and in accordance with the training data.

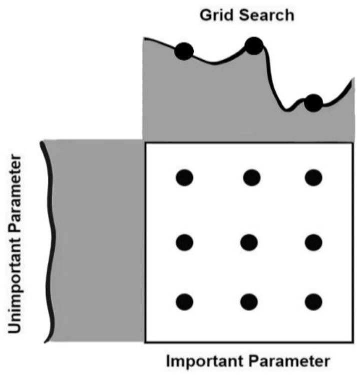

Figure 4. Grid Search Illustration

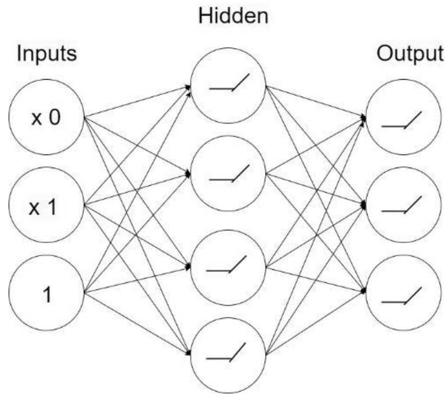

Figure 5. Neural Network Layers

Based on Figure 5, Artificial neural networks (ANNs), another name for neural networks, are computer networks that are inspired by biological neural networks, which are intricate networks of neurons in the human brain (systems of nodes and connections between nodes) [11].

A subfield of computer science called machine learning includes neural networks, or computer models that mimic the structure and functions of the human brain. Neurons comprise neural networks, which are basic processing units arranged in layers. These neurons are linked together by connections that have particular weights or values.

Helps in selecting the best model and hyperparameter settings by comparing the performance of various models or model configurations on test data. It is used to train the model to recognize patterns in the data and minimize errors in the training data by optimizing the Learning rate, Number of Epoch and Batch Size hyperparameters. Choosing the optimal hyper-parameter configuration for machine learning models directly influences their performance [14].

Determining the best model in Deep Learning involves a series of systematic steps to select, train, evaluate and compare various model configurations to find the most optimal model.

Training data based on the model, this process is the stage where the model learns from the given data to make predictions or decisions. This training involves various steps and techniques that aim to minimize errors and improve model accuracy.

Predictions may approach the actual values and will certainly contain errors, but in reality, they will never be 100% accurate. As a result, determining the degree of prediction error is crucial. Calculated to find the mean absolute difference (MAE) between the expected and actual values. It provides an overview of the total number of expected errors.

$$\frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \quad (1)$$

In Formula 1 for Mean Absolute Error n represents the number of observations, y_i represents the actual value, and $\hat{y}_i$ represents the predicted value.

The mean squared error is the average of the squared differences between the expected and actual values or MSE. because before being summed, the numbers are squared, and MSE places more emphasis on larger errors. This objective metric is perfect for determining which model performs best, but it does not reveal much about what makes a model good or bad. It offers minimal understanding of what constitutes "good" or "bad" model performance [15].

$$\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \quad (2)$$

In Formula 2 for Mean Squared Error n represents the number of observations, y_i represents the actual value, and $\hat{y}_i$ represents the predicted value.

R-Squared (R^2) (3)

In Formula 3, R^2 calculates how much of the variance in the dependent variable the model can account for. The better the model predicts the data, the higher the R^2 number, which goes from 0 to 1. The coefficient of determination (R-squared) has no interpretive limitations and is a more honest and informative metric when used to evaluate regression analysis in any scientific field [16].

$$1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \quad (4)$$

In Formula 4 for R-squared n represents the number of observations, y_i represents the actual value, $\hat{y}_i$ represents the predicted value, and $\underline{y}$ is the mean of y_i.

3. Results and Discussions

3.1 Data Understanding and Data Transformation

The dataset that will be used for execution is created during the Data Preparation stage by merging data from the years 2018 through 2022. After choosing and altering the columns' and rows' format, the dataset will be shown. After that, the dataset is divided into two subsets: training and testing, wherein 80% and 20% of the data, respectively, are used for training. In deep learning, the model is trained on 80% of the data, with the remaining 20% being used for testing to make sure the predictions are accurate and consistent with the training set.

In order to ensure that the collected data is in the optimal structure for training deep learning models, data transformation techniques are applied to the dataset's column and row shapes during the data understanding phase. Values will be standardized, relevant features will be modified, and the data structure will be reorganized. To improve the performance, accuracy, and efficiency of the deep learning model, as well as its capacity to produce more perfect results and align with the intended analytical objectives, the data must become more structured and appropriate for the model's requirements. An initial overview of the form and state of the raw data that will be utilized in the analysis is given by the sample of data in Table 2 which is provided prior to the data transformation procedure. The data is still in its original format because it hasn't undergone any modifications or edits at this point.

Before:

Table 2. Sample table before the Data Transformation process.

Items	Year	Assam	Bihar
Cost of Cultivation (Rs./Hectare) A1	2018	60237.33	51195.4
Cost of Cultivation (Rs./Hectare) A2	2018	60254.38	51195.4
Cost of Cultivation (Rs./Hectare) B1	2018	61527.19	52359.03
Cost of Cultivation (Rs./Hectare) B2	2018	81657.92	75055.82

After:

Table 3. Sample table after the Data Transformation process

State	Year	Cost of Cultivation (Rs./Hectare) A1	Cost of Cultivation (Rs./Hectare) A2
Assam	2018	60237.33	60254.38
Bihar	2018	51195.4	51195.4
Gujarat	2018	72798.7	74145.12
Himachal Pradesh	2018	43643.79	45629.42
Uttar Pradesh	2018	54887.97	56589.27
West Bengal	2018	88515.79	88557.23

The data in Table 3 have been processed and modified to meet the requirements of additional analysis or model as shown by the data samples, which have undergone the data transformation process.

3.2 Split Data with Grid Search

A technique that discretizes each hyperparameter range and thoroughly analyzes each possible value combination is known as grid search. In grid search, within the box constraints, hyperparameter values, both integer and numeric, are typically distributed equally. The number of distinct values for every hyperparameter is the grid resolution [17].

Grid Search is used here to classify data into a table based on the classification of years according to the cities in the table, and then add hyperparameters to be optimized using Learning Rate, Number of Epochs, and Batch Size. The Learning Rate is the process of training a model using the gradient descent method. The learning rate determines the size of the steps taken to change the weights or other parameters of the model during training. This learning rate is also a de facto optimization technique for neural networks. The technique begins with large-scale training and is repeated multiple times. It is empirically analyzed to support generalization and optimization [18].

The number of epochs controls how many times the model will process the whole dataset while it is being trained. The model's parameters, including weights and biases, are adjusted depending on the model's error on each batch as it learns from the complete dataset throughout each epoch. Epochal periods indicate how many times a machine learning process has been run through. A longer duration translates into more hours needed to do the task [19].

The quantity of images needed to train a single forward and backward pass is referred to as the batch size. It's among the most important hyperparameters [20]. The quantity of data samples utilized in a single model training iteration is also known as batch size. The dataset is divided into smaller groups, and Batch Size determines how many data samples will be fed to the model at one time during an iteration.

Training data is denoted by x, which includes all columns except the total cost, and y is the target, which is the total cost. The train_test_split function divides the data into 80% training, deep learning models use this dataset as their primary learning element. The model will discover patterns, trends, and feature correlations from this data and 20% testing to evaluate the learned model.

3.3 Classification Model Building

Based on prior research knowledge and experience, the researcher selected these hyperparameter values because they represent a useful range and demonstrate a fair trade-off between computational efficiency and model result quality:

Learning Rate (e.g. [0.001, 0.01, 0.1]): This range was chosen because it covers a wide range of learning rates. Low values (0.001) are suitable for models that require stable learning or in cases of high divergence risk. Larger values (0.01 and 0.1) speed up the convergence process, which is suitable for already stable models or large datasets. This range allows for considerable exploration without making the tuning process too complex.

Epochs (e.g. [10, 20, 30]): This range of values is chosen to provide a choice between short and longer training. The number 10 allows fast training, especially if the dataset is large and the model is simple, thus avoiding the risk of overfitting. Numbers 20 and 30 provide options for more complex models or smaller datasets, where more iterations may be required to learn deep patterns. These values help to find the optimal number of epochs without too much or too little training.

Batch Size (e.g. [16, 32, 64]): This batch size range was chosen because it represents a balance between computational performance and model accuracy. Small batches (e.g. 16) allow for more frequent parameter updates, which can improve accuracy, while larger batches (e.g. 64) utilize computational resources more efficiently, allowing for faster training. This range gives researchers the flexibility to customize speed and accuracy.

Hyperparameters are optimized through Grid Search with the results shown:

```
param_grid = {'learning_rate': [0.001, 0.01, 0.1],
              'epochs': [10, 20, 30],
              'batch_size': [16, 32, 64]}
```

With these numbers, researchers have relevant and flexible options for conducting experiments so as to achieve the optimal hyperparameter configuration for the model.

3.4 Best Model

The results from this parameter optimization are used to determine which model performs best, and the best parameters obtained from this search are shown in Table 4.

Table 4. Table of Best Parameters

Best Parameters			
Batch Size	Epoch	Learning Rate	Best Score
64	30	00.01	-1382753909

The dataset is partitioned into multiple batches during the training phase, each having 64 data samples, as indicated by the batch size hyperparameter. The model updates its weights following each batch. The number of epoch hyperparameters specifies that the full dataset will be used for training thirty times when there are thirty epochs. As a result, the model has plenty of opportunity to identify patterns in the data and gradually optimize its weights at each iteration, enhancing the model's functionality and precision of predictions. Furthermore, the parameter that regulates the size of the step made by the parameter optimization in updating the model weights and determines how quickly or slowly the model will learn from the data during the training process is the learning rate hyperparameter. The model displays a result of 00.01, indicating that it will change its weights by a step of 0.01 throughout each training cycle.

3.5 Training Data

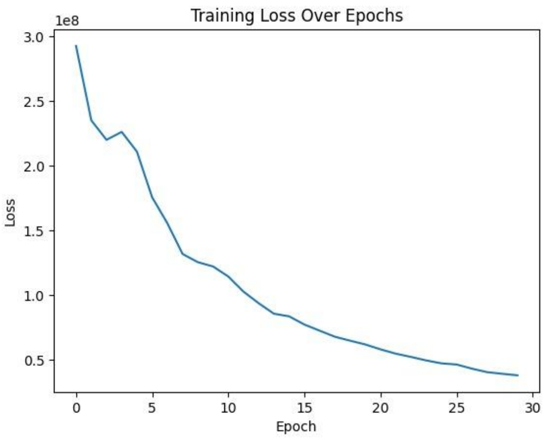

Figure 6: Loss Reduction Results Based on Number of Epochs

The results of the Number of Epochs testing, as shown in Figure 6, can be categorized as follows:

Epoch 1-5:

At the beginning of training during epochs 1-5, there is a significant decrease in the loss value. This indicates that the model quickly learns the patterns in the data and starts reducing prediction errors.

Epoch 6-15:

During epochs 6-15, fluctuations in the loss value are observed. This could be due to variations in the data or perhaps more subtle changes in the patterns identified by the model. There are substantial changes in the loss value during some epochs.

Epoch 16-25:

In epochs 16-25, there is further reduction in the loss value, indicating that the model continues to optimize its parameters and improve its predictions.

Epoch 26-30:

Although the loss value continues to decrease, the rate of reduction seems to slow down towards the end of the training (Epochs 26-30). This may indicate that the model is nearing convergence and there are no significant improvements in performance after the last few epochs.

Convergence is the point at which the model has achieved optimal or near-optimal performance by epochs 26-30, the model is considered to have converged or reached convergence.

Table 5 displays the evaluation findings derived from the MAE, MSE, and R^2 computations:

Table 5. Evaluation Results of MAE, MSE, and R^2 Calculations

Metrics		
MAE	MSE	R^2
22526.07	996274728.7	0.7076

The researcher's model yielded a mean absolute error (MAE) of 22526.07 for its performance. This indicates that there is an average absolute error of 22526.07 between the observed data's actual value and the value predicted by the model. This shows that the average deviation between the model's predictions and the actual values is 22526.07, which is the difference between each dataset's individual values and the dataset's average value.

This model yields a Mean Squared Error (MSE) of 996274728.7. The average square of the variation between the expected and actual values is determined by the MSE metric. With a greater emphasis on the more important errors, a value of 996274728.7 indicates a considerable squared difference between the actual value and the value predicted by the model. This value reflects the amount of prediction error.

And the obtained R-squared (R^2) value is 0.7076. A statistic called R-squared indicates how well the model can account for the variation in the observed data. With an R^2 value of 0.7076, the model can account for roughly 70.76% of the variation in the real data. Stated otherwise, 70.76% of the data variability can be accounted for by the model, suggesting that the model has a respectable degree of predictive accuracy for the true values.

3.6 Evaluation with Feature Importance

Feature Importance refers to the significance of a feature for the model's ability to predict outcomes, regardless of the direction or form of the feature's impact (e.g., linear or nonlinear relationships) [21].

The findings of the Atribute Feature Importance analysis, based on Figure 7, are presented in the following figure, which shows how much each feature adds to the predictive model's capacity for correct prediction. It provides comprehensive details about the significance of each feature or attribute in the model that was employed. And the accuracy of the values derived by examining various aspects of Atribute Feature Importance is depicted in the accompanying figure, which offers a comprehensive understanding of the relative contributions of each feature and attribute to the overall performance of the model.

Figure 8 shows the other visualization of Feature Importance. From this figure, it can be concluded that the value of Cost of Cultivation 2 has the greatest influence, with an approximate value of 0.1734. Other values following it include 0.1370 for Cost of Cultivation B2, 0.1081 for Cost of Cultivation C2 Revised, 0.0859 for Operational Cost, 0.0822 for Cost of Cultivation C1, 0.0715 for Fixed Cost, and 0.0615 for Fixed Cost on Rental Value of Owned Land.

This document concludes that the biggest influence on the cost of potato farming is the value of the cost of cultivation C2, which is the result of the calculation of the components in the cost of potato farming, where the Cost of Cultivation C2 is the total cost value that includes all direct expenses, interest on fixed capital, land rental value (both owned and rented), and compensation for family labor. value Cost of Cultivation C2 represents the most comprehensive cost of cultivation, which includes all real and calculated costs, to describe the total cost of farming.

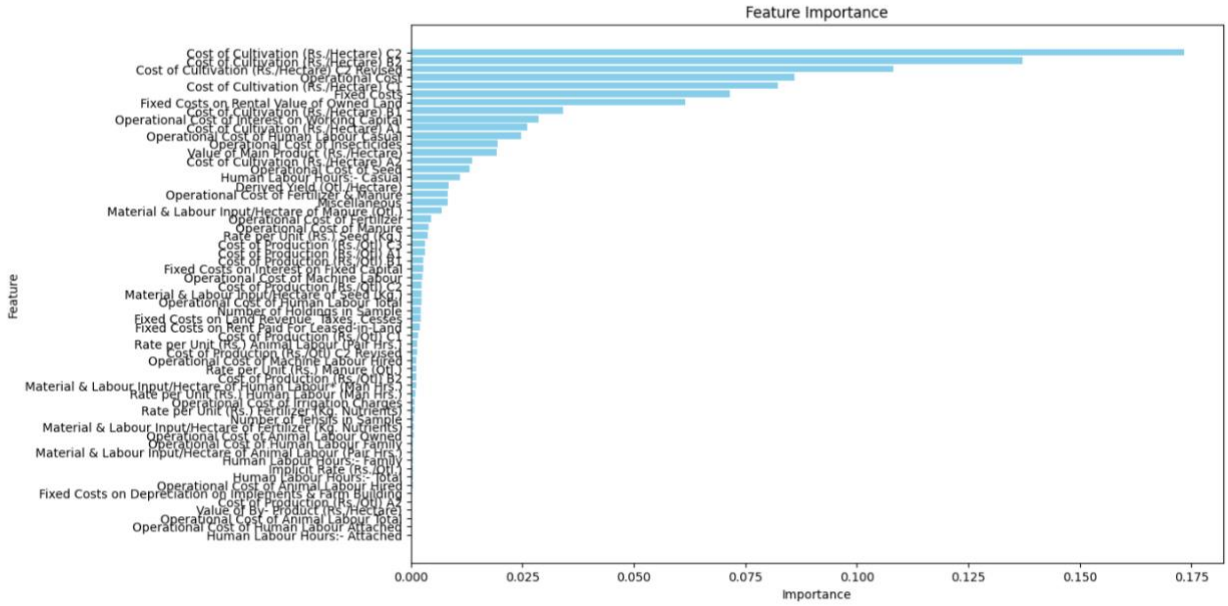

Figure 7. Display of Attribute Feature Importance Results

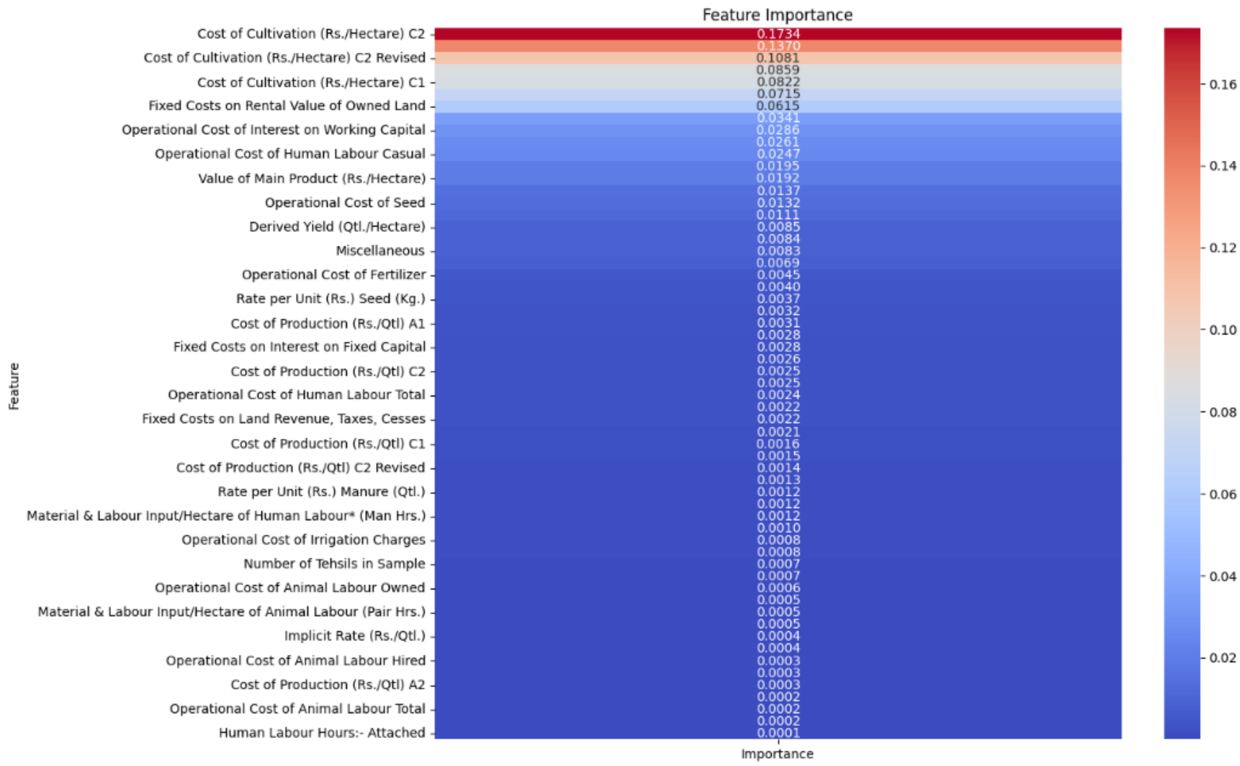

Figure 8. Feature Importance in Other Visualizatio

The analysis of the previous study can be expressed by describing the need for improved agrarian and social economic crisis support in India, and this document describes a more technical and specific cost analysis and in-depth understanding of the cost of cultivation. Cost of Cultivation C2 that can help in cost efficiency in potato cultivation, which is a complementary perspective in solving the problem of profitability in agriculture.

4. Conclusions

Based on the research results, the prediction from the best model obtained through Hyperparameter Optimization for this deep learning process is with the model settings of batch_size: 64, epochs: 30, and learning_rate: 0.01. After executing the model, the graph showing the loss reduction across the epochs indicates a significant decrease. The model continues to optimize its parameters, and by the end of the number of epochs, specifically epochs 26-30, it has reached convergence or a performance level that is close to the optimal value, which can be considered successful as the score achieved is -1,382,753,909. The research results regarding Feature Importance show that the components with the greatest influence on predicting agricultural cultivation costs, in descending order, are Cost of Cultivation 2, Cost of Cultivation B2, Cost of Cultivation C2 Revised, Operational Cost, Cost of Cultivation C1, Fixed Cost, and Fixed Cost on Rental Value of Owned Land. It can be concluded that Cost of Cultivation 2 has a significant impact. Therefore, farmers should focus more on calculating these components, which will help them leverage opportunities and achieve high-quality potato production, as noted by the Directorate of Economics and Statistics, Department of Agriculture and Farmers Welfare, Ministry of Agriculture and Farmers Welfare, Government of India. The dataset is restricted to the Indian region, the commodities used are confined to potatoes, and there are difficulties in predicting more dynamic costs. These are the study constraints in this document. Recommendations that can be made for future research, especially a thorough analysis of the available datasets.

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