ENHANCING PREDICTION OF SUITABLE CROP USING NMF AND RANGER OPTIMIZATION TECHNIQUESWITH CNN

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ABSTRACT

Accurate prediction of crop is necessary to maximize agricultural output and advance environmentally friendly farming methods. A significant natural resource, soil is essential for flood protection, drought mitigation, food production, and water purification. In order to improve prediction accuracy, this paper proposes a hybrid machine learning (ML) framework that combines the Ranger Optimization Technique with Non-Negative Matrix Factorization (NMF) for dimensionality reduction and feature extraction. High-dimensional agricultural datasets are efficiently broken down into useful components by NMF, and the predictive model is optimized for better performance using Ranger Optimization. Real-world datasets including soil characteristics, meteorological conditions, and historical crop yield data are used to assess the suggested framework. With an accuracy of 91%, experimental results show notable gains in prediction accuracy, computational efficiency, and model robustness when compared to conventional methods. This method offers a potent data-driven precision agricultural solution that facilitates better decision-making, efficient use of resources, and increased food security.

Keywords: Crop Prediction, Crop Recommendation, Non-Negative Matrix Factorization and Ranger Optimization.

1. INTRODUCTION

Agriculture provides us with food, feed, and fiber, as well as clothing, lumber for our homes, and organic materials that grow in the soil or a substitute for it. Agriculture shows the major role in the national economy. For the simple reason that it serves many purposes, agriculture is crucial to any country. First of all, it serves as a nation's foreign exchange. This is accomplished through agricultural product exports. Agriculture also serves as a ready market for the industries. This is carried out when the equipment is acquired from the industries, thereby aiding in the growth of that country. Although a number of factors influence the agricultural sector, the primary goal of agriculture is to produce food for the nation's citizens [1].

Data mining is the act of wading through large amounts of data in order to extract information or knowledge using a variety of statistical and computational techniques. The distribution of unstructured data, semi-structured data, and structured data in the databases, data warehouses, and data lakes. The main goal of data mining [2] is to find hidden patterns and relationships in data that may be used to inform decisions or predictions. This is analyzing the data in multiple ways — being it anomaly detection, regression, association rule mining, clustering, and classification, etc. Applications for data mining are numerous and span a number of sectors, including marketing, finance, healthcare, and telecommunications [3]. Data mining, for instance, can be used in marketing to pinpoint marketing campaigns and identify customer segments, and in healthcare to determine disease risk factors and create individualized treatment regimens [4].

Traditional statistical methods for crop yield prediction, though effective in some contexts, are often not up to the task of handling high-dimensionality and intricate relationships within these datasets [5]. It has been seen that machine learning techniques have become great tools to bridge such limitations, providing the means for meaningful insights into complex data. Among these are Non-Negative Matrix Factorization (NMF), which performs dimensionality reduction while preserving non-negativity constraints inherent in most agricultural datasets. NMF breaks down high-dimensional data into easier-to-interpret components, hence allowing efficient feature extraction and increasing model performance [6].

Machine learning (ML) is significant decision support for crop yield prediction, including the support of decisions like what crops to grow and what to do during the growing season of the crops [7]. The agricultural data refers to the crop yield based on inadequate and sufficient soil nutrients and climate changes, for suggesting crop types or additional nutrients, to yield the highest level of production in machine learning [8].

With the development of the internet, people are increasingly turning to online applications to meet the majority of their needs. They don't have much free time to devote to the selection process in the interim. As a result, there is an increasing need for recommender systems to help address this problem. These systems are effective at giving users tailored suggestions on a variety of products to make their tasks easier. The goal of this research is to create a tree data structure-based recommender system for farmers [9][10].

The sector that contributes to our nation's economic expansion is agriculture. However, this lags behind when it comes to utilizing new machine learning technologies. Therefore, our farmers ought to be familiar with all the latest ML technologies and other innovative methods. These methods aid in achieving the highest possible crop yield [11].

The crop wise dataset is taken for expecting the recommended crop using soil data. Non-Negative Matrix Factorization (NMF) [12], Ranger Optimization and the combined Non-Negative Matrix Factorization with Ranger Optimization are used to extract features from the soil dataset. The deep learning model namely CNN [13] is used to recommended crops.

2. LITERATURE REVIEW

The method developed a framework that consists of a unique hybrid feature choosing method and an optimized Support Vector Regressive (SVR) model. Their method integrates K-means clustering and correlation-based filters to reduce dataset dimensionality, followed by a hybrid feature selection strategy combining Fisher Score, Mutual Information Gain, and Recursive Feature Elimination. The Improved Crayfish Optimization Algorithm (ICOA) is then employed to fine-tune the SVR model's hyperparameters, resulting in superior prediction accuracy compared to existing methods [14]. In their model the importance of feature optimization for crop yield prediction models is stressed. To the feature selection and model parameter optimization through genetic algorithms, they proposed an improved genetic algorithm. They demonstrated that this method is superior to standard ones by comparison. Their comparative analysis highlighted significant improvements in prediction accuracy and computational efficiency, underscoring the benefits of optimized feature selection in agricultural forecasting [15].

IoT-Based Hybrid Attention Model on Crop Yield Prediction made a hybrid attention model by taking this three-step method and hitting its six-o'clock position with a sailfish optimizer improves the in-degree. This model integrates data from various IoT sensors and employs a hybrid attention mechanism to focus on relevant features, enhancing prediction accuracy. The improved sailfish optimizer further refines the model parameters, demonstrating the effectiveness of combining IoT data with advanced optimization techniques in agricultural predictions [16]. Two-Stage Classifiers for high altitude gardens and cooperatives presented a two-level classifier framework that, using meta-heuristic methods selects the global optimal model.

Their method involves an initial feature selection phase using improved correlation techniques, followed by classification using a combination of machine learning algorithms. The framework's effectiveness is enhanced through the application of a Dynamic Oppositional-Based Sine Cosine Algorithm (DOSP), which optimizes the classifiers' parameters, resulting in improved prediction performance [17].

Optimized Machine Learning Framework focused on crop disease detection, proposing an optimized machine learning framework that combines feature extraction with the Krill Herd Optimization algorithm. By integrating Random Forest classifiers and optimizing feature selection, their approach enhances the accuracy of disease detection, which is crucial for timely intervention and yield preservation [18]. Crop Yield Prediction model applied deep learning techniques to predict crop yields by analyzing satellite imagery. Convolutional Neural Networks (CNNs) were employed to extract spatial features from the images, providing accurate yield estimations across diverse geographic regions [19].

A study explored the use of ensemble learning methods, combining multiple ML algorithms to improve the robustness and accuracy of crop yield predictions. Techniques such as bagging and boosting were utilized to aggregate predictions from various models [20]. Application of Random Forests employed Random Forest algorithms to analyze complex agricultural datasets, demonstrating the method's effectiveness in handling large feature sets and providing reliable yield predictions [21].

A study utilized Support Vector Machines (SVMs) for crop classification and yield estimation, highlighting the algorithm's capability to manage high-dimensional data and deliver precise predictions [22]. Remote Sensing integrated data into crop yield prediction models, enhancing the spatial resolution and accuracy of forecasts. This approach allowed for the monitoring of crop health and yield estimation over large agricultural areas [23].

3. PROPOSED MODEL

The proposed model integrates Non-Negative Matrix Factorization (NMF) and Ranger Optimization for enhanced crop prediction accuracy. It begins with three primary datasets: Soil

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Properties Dataset, Weather Conditions Dataset, and Historical Crop Yield Dataset. These datasets provide crucial agricultural parameters such as soil nutrients (N, P, K), pH levels, moisture content, temperature, rainfall, and crop yield records. In this paper, the NMF, Ranger Optimization and the combined NMF with Ranger Optimization techniques were used to extract the features. the proposed crop prediction framework is implemented using Python, leveraging libraries such as Pandas and NumPy for data preprocessing, scikit-learn for NMF to reduce dimensionality, and PyTorch for building and training a Convolutional Neural Network (CNN) enhanced with Ranger Optimization. It starts with preprocessed raw agricultural data, comprising information on soil, weather, and crop yields, cleaned and normalized and feature scaled to make the data consistent and of high quality. NMF decomposes a high-dimensional dataset into meaningful components that reconstruct important features for prediction. These features are then fed into the CNN, which captures complex patterns and relationships, while the Ranger Optimizer refines the model by combining Rectified Adam (RAdam) and Lookahead mechanisms for efficient and robust learning. The results are visualized to validate the accuracy of the model's prediction. The integration of dimensionality reduction, deep learning, and advanced optimization ensures a computationally efficient and accurate simulation for crop prediction.

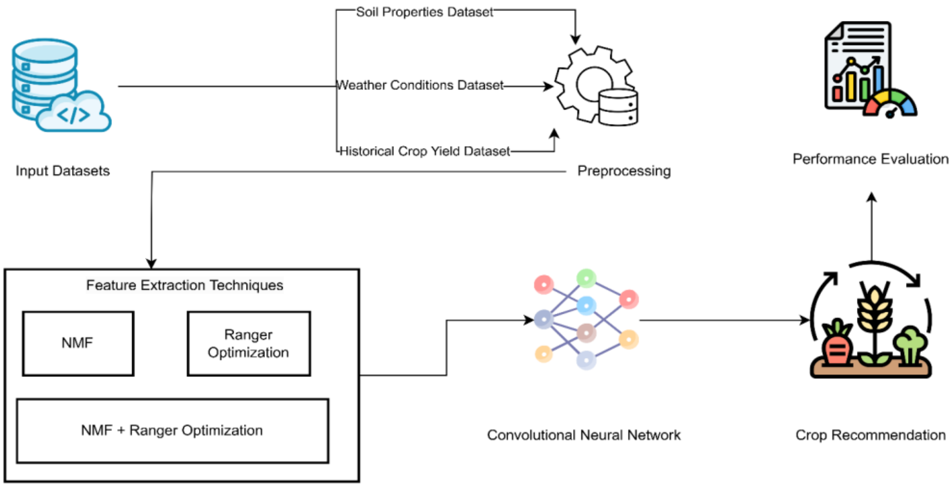

Fig. 1.1. Block diagram of the Proposed work

The Fig. 1 shows the block diagram of the proposed work. In the feature extraction phase, the model employs NMF to decompose high-dimensional data into meaningful latent features, capturing essential patterns while reducing noise. Simultaneously, Ranger Optimization is used to fine-tune the feature selection process, improving model performance. The combined approach, NMF + Ranger Optimization, further enhances feature relevance and predictive power.

The extracted features are then fed into a Convolutional Neural Network (CNN), which learns complex relationships between environmental factors and crop yield. The CNN processes the optimized feature set to generate precise crop recommendations. By leveraging deep learning with an optimized feature selection mechanism, the proposed model achieves higher prediction accuracy, computational efficiency, and robustness compared to traditional machine learning methods.

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Step 1: Data Collection

The data collection process involves gathering real-world agricultural datasets that contain comprehensive information on soil properties [24], weather conditions [25], and historical crop yield [26] data. Soil properties include key attributes such as nutrient levels (e.g., nitrogen, phosphorus, potassium), pH levels, and moisture content.

$$S = \{s_1, s_2, \dots, s_n\} \quad (1)$$

Where s_i represents soil attributes like nutrients (N, P, K), pH level (pH), and moisture content.

$$W = \{w_1, w_2, \dots, w_m\} \quad (2)$$

Where w_i includes parameters like temperature (T), rainfall (R), and humidity (H).

$$Y = f(S, W) \quad (3)$$

By collecting these features, we prepare a dataset for machine learning, where each sample consists of a feature vector:

$$X = [S, W] \Rightarrow Y \quad (4)$$

The goal is to predict Y given X.

Step 2: Data Preprocessing

Data preprocessing is an important step that needs to be taken in order for the data set to be clean, consistent and ready for machine learning. First, data cleaning is performed to handle missing values and outliers. Missing values can be imputed using statistical methods such as mean, median, or mode, represented as:

$$x_i = \frac{\sum_{j=1}^{n} x_j}{n}, where\ x_i\ is\ a\ missing\ value \quad (5)$$

Outliers are detected using techniques like the Interquartile Range (IQR):

$$IQR = Q3 - Q1$$

Next, the dataset is normalized using Min-Max scaling to ensure all features are within a common range, typically between 0 and 1:

$$x' = \frac{x - x_{min}}{x_{max} - x_{min}} \quad (6)$$

Finally, categorical variables such as crop type or soil type are encoded using one-hot encoding, converting each category into a binary vector. For example, a categorical variable with three categories {A, B, C} would be represented as:

$$A = [1, 0, 0], \quad B = [0, 1, 0], \quad C = [0, 0, 1] \quad (7)$$

These preprocessing steps ensure that the dataset is clean, scaled, and appropriately formatted for input into machine learning model.

Step 3: Dimensionality Reduction using NMF

Non-Negative Matrix Factorization

The feature matrix's dimensionality can also be decreased using the linear dimensionality reduction method known as Non-Negative Matrix Factorization (NMF). A matrix factorization technique called nonnegative matrix factorization requires that the matrices be nonnegative. We must elucidate the fundamental intuition between matrix factorization in order to comprehend NMF. Every feature that NMF generates is a linear combination of the initial set of attributes. Every feature has a collection of coefficients that indicate how much weight each attribute has on the feature. Every numerical attribute and every unique value of every categorical attribute has its own coefficient. All of the coefficients are positive.

NMF factorizes A, a matrix that is m x n, into two nonnegative matrices W and H of m x k and k x n respectively by using only non-negative elements. Written in matrix terms, we say that unnaturally elements of matrix A are defined as above.

$$Amxn = Wmxk\ Hkxn \qquad (8)$$

where A is the original input matrix, W is the feature matrix, H is the coefficient matrix and k is the low rank approximation of A. This approach is frequently used for a variety of NLP tasks, including feature reduction in facial recognition. The goal for dimensionality reduction and feature extraction is NMF. Given a lower dimension value of k, then the W ∈ Rm×k and H ∈ Rn×k that set forth after NMF seeks to achieve only non-negative components means "k."

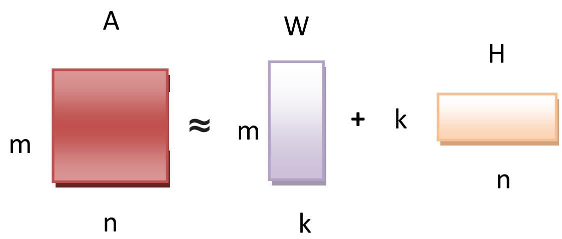

Figure 2: Non-Negative Matrix Factorization

Reduce dimension and extract features - those are the goals of NMF. When the dimension is taken as k as indicated in Fig 2, the object of NMF is to find two matrices, W$\in Rm \times k$ and $H \in Rn \times k$, which only contain non-negative elements. Respectively reduced factorised submatrices of the product matrix with dimensions that are much smaller than its whole can be got by applying NMF.Every column of the matrix W stand for a set of the hidden features, and every column of the matrix H stand for the coordinates of a data point in how matrix W.This is the straightforward assumption which NMF makes: that your original input is made up of these hidden featuresSimply speaking, it contains the weights related to the matrix W; this is the objective of NMF, and AAdditive combination that.Non-negative vectors represented as columns in W can approximate each data point represented as a column in A.

Step 4: Model Training Using CNN and Ranger Optimization

In this step, a **1D Convolutional Neural Network (CNN)** is used to model the complex relationships between soil properties, weather conditions, and historical crop yields. Unlike traditional machine learning models, CNNs can effectively capture localized patterns and interactions within the data. By applying convolutional operations on structured data, the CNN extracts relevant features that contribute to accurate crop predictions.

Data Representation and Input Processing

The input dataset is organized as a one-dimensional sequence:

$$X = [x_1, x_2, \dots x_n] \qquad (9)$$

Where, X represents the feature vector with n attributes, Each x_i is a normalized feature value, Y denotes the corresponding crop yield.

The dataset is split into training and testing subsets using a ratio such as **80:20** to ensure proper model evaluation.

Convolutional Operation

A convolutional layer applies a set of filters (kernels) to the input data. Each filter extracts localized patterns by performing a convolution operation, defined as:

$$z_i = \sigma\left(\sum_{j=1}^{k} W_j \cdot X_{i-j+1} + b)\right) \qquad (10)$$

Where, $z_i \rightarrow$ output of the convolution layer, $W_j \rightarrow$ Filter weight, $k \rightarrow$ Kernel size, $b \rightarrow$ Bias term, $\sigma \rightarrow Activation\ function, commonly\ ReLu.$

$$\sigma(x) = (0, x) \qquad (11)$$

The convolution layer is followed by a pooling layer to reduce the dimensionality of the feature maps, improving computational efficiency and reducing overfitting. **Max pooling** is often applied using the following equation:

$$P_i = \{ Z_j : j \in Window\} \qquad (12)$$

Where the window size defines the region over which the maximum value is taken.

Fully Connected Layer and Output Generation

The feature maps from the final pooling layer are flattened into a single vector and passed through one or more fully connected layers. The output layer uses a linear activation function to generate the final crop yield prediction:

$$\hat{Y} = W^T P + b \qquad (13)$$

Where, $\hat{Y}$ = Predicted crop yield, W = weight vector, P = Flattened feature vector from the previous layer, b = bias term.

Ranger Optimization Process:

1. **Initialization:** Generate an initial population of hyperparameter configurations θ1,θ2,…,θn using a random search strategy.
2. **Evaluation:** Train the model using each configuration and compute the objective function (e.g., prediction accuracy or mean squared error):

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$$L(\theta) = \frac{1}{N}\sum_{i=1}^{N} \left(Y_i - \hat{Y}_i\right)^2 \tag{14}$$

$where\ Y_i$ is the actual crop yield and $\hat{Y}_i$ is the predicted crop yield.

1. **Adaptive Search:** Apply an adaptive mechanism to adjust the search space by focusing on promising regions, reducing unnecessary exploration.
2. **Selection:** Choose the best-performing hyperparameter configuration that minimizes the loss function:

$$\theta^* = arg\ arg\ L(\theta) \tag{15}$$

The integration of 1D CNN for feature extraction and Ranger Optimization for hyperparameter tuning results in a robust crop prediction model. This approach leverages CNN's ability to capture intricate patterns in the data while ensuring optimal performance through efficient hyperparameter optimization. The proposed framework is expected to deliver accurate, reliable crop yield predictions, enhancing decision-making in agricultural planning and resource management.

4. RESULTS AND DISCUSSION

Dataset Description

The real time soil dataset were collected from Manur 2019-2020. Manur, also known as Manoor, is a village in Manur Taluk, Tirunelveli District, Tamil Nadu, INDIA. It is located between Sankarankovil and Tirunelveli. North of Tirunelveli, this village is 26 kilometers away. The soil dataset contains 943 records with various villages data includes 17 attributes which about 70% data were used for training and about 30% were used for testing. The features were fed into CNN for crop recommendation. In this proposed work, the combined features with CNN gives good performance in predicting crop.

Performance Measures

The proposed work recommends crop using the real time soil dataset with the CNN using the features extracted from the various feature extraction techniques. The confusion matrix predicts the accuracy of every crop. The soil data be trained and tested effectively; precision, recall, f-score and accuracy of crop prediction and recommendation are

$$Precision\ = TP\ /\ (TP + FP) \tag{16}$$

$$Recall\ = TP\ /\ (TP + FN) \tag{17}$$

$$F - score\ = 2\ (Precision\ x\ Recall)\ /\ (Precision\ +\ Recall) \tag{18}$$

$$Accuracy\ = (TP + TN)\ /\ (TP + TN + FP + FN) \tag{19}$$

Table 1: Overall Comparison of Performance Metrics

Features	**Model**	**Accuracy (in %)**	**Precision (in %)**	**Recall (in %)**	**F-score (in %)**
NMF		88	84	81	82

Ranger Optimization	Convolutional Neural Network	86	84	80	82
Combined		91	89	87	88

Table 1 presents a comprehensive comparison of performance metrics, including Accuracy, Precision, Recall, and F-score, for different approaches used in the study.

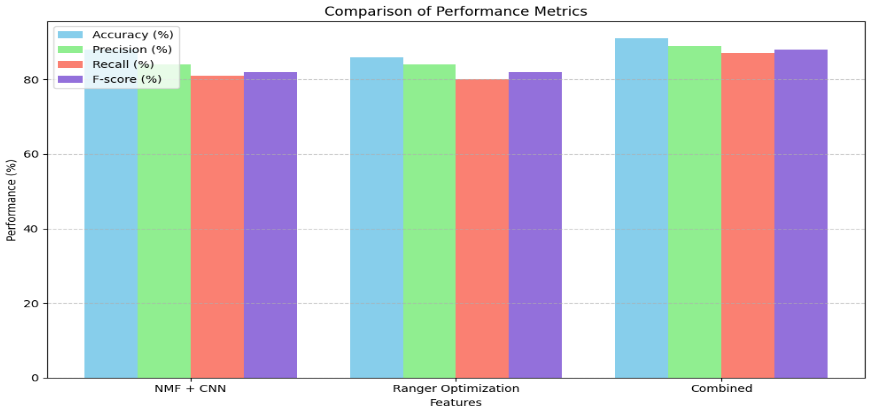

Figure 3: Overall Comparison of Proposed Metrics

From Fig 3, the Non-Negative Matrix Factorization (NMF) combined with a Convolutional Neural Network (CNN) achieved an accuracy of 88%, with a precision of 84%, recall of 81%, and an F-score of 82%. When the Ranger Optimization technique was applied, the accuracy slightly reduced to 86%, while the precision and recall remained at 84% and 80%, respectively, leading to an F-score of 82%. However, the combined approach, which integrates both NMF and Ranger Optimization, demonstrated superior performance. It achieved the highest accuracy of 91%, with a precision of 89%, recall of 87%, and an F-score of 88%. This indicates the effectiveness of the combined strategy in enhancing the model's predictive capability by leveraging the strengths of both methods.

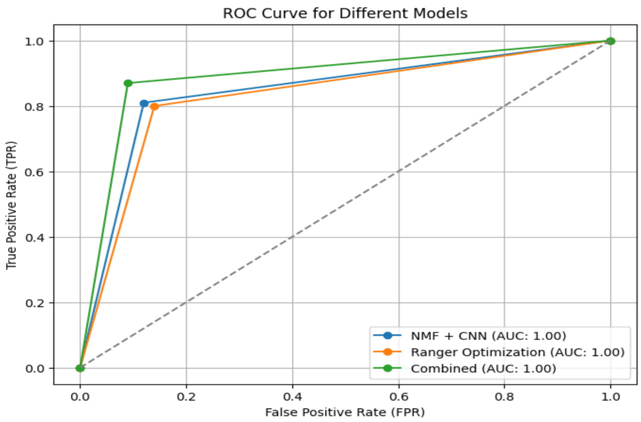

Figure 4: ROC Curve

From Fig 4, the ROC curve compares the performance of the NMF + CNN, Ranger Optimization, and Combined models using True Positive Rate (TPR) and False Positive Rate (FPR). The Combined model shows the highest AUC, indicating superior classification performance. The diagonal line represents a random classifier (AUC = 0.5).

5. CONCLUSION

In order to improve prediction accuracy, this paper suggests a hybrid machine learning strategy that combines the Ranger Optimization Algorithm with NMF for dimensionality reduction and feature extraction. While Ranger Optimization optimizes the prediction model for optimal performance, the NMF technique efficiently breaks down high-dimensional agricultural datasets into meaningful components. The raw dataset preprocessed and NMF, Ranger Optimization and combined NMF with Ranger Optimization is used to extract the features, the features are fed into CNN is used to recommend the crops with the soil dataset. When compared to conventional techniques, the results show notable gains in prediction accuracy, computational efficiency, and robustness where combined NMF with Ranger Optimization yields better accuracy of 91%. The evaluation results clearly show a marked improvement in accuracy, precision, recall, and F-score, which indicates that this approach may be useful for precision agriculture. The proposed framework presents a promising avenue for using advanced machine learning techniques to support data-driven agricultural practices, leading to more efficient crop management and sustainable farming.

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