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CROP YIELD PREDICTION USING DEEP LEARNING

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ABSTRACT – The identification of an appropriate crop and fertilizer for every soil type is one of the key problems of modern agriculture. In the past, such decisions were based on experience, but technological progress today enables data-driven decision-making. This research recommends adopting a deep learning-based approach with a Lightweight Gradient Convolutional Neural Network (LGCNN) to classify images of soil into Black, Cinder, Laterite, Peat, and Yellow Soil. Training data are accessed from open databases and pre-processed using noise removal, segmentation, and feature extraction. Post-classification, soil types are mapped to pre-defined crop and fertilizer recommendations using a pattern-matching algorithm. LGCNN is more efficient compared to traditional models like Random Forest and is more accurate (98.96%). The system enhances precision farming using optimized resource allocation, improved crop yield, and sustainable agriculture. By combining machine learning and soil science, deep learning has the capability to significantly enhance farm output while not jeopardizing agricultural sustainability.
Keywords: Deep Learning, Lightweight Gradient Convolutional Neural Network (LGCNN), Crop Recommendation, Fertilizer Recommendation, Image Processing.

1. INTRODUCTION

Agriculture is one of the key drivers of global food security, and optimizing crop choice according to soil characteristics is important to achieve maximum yield and sustainability. Crop and fertilizer selection traditionally depended on farmers' experience, which was often wasteful due to heterogeneity in soils and climatic conditions. However, with recent advances in deep learning and artificial intelligence, more accurate and data-driven farming decisions are possible.

This paper presents a deep learning-based crop yield forecasting system that utilizes Lightweight Gradient Convolutional Neural Networks (LGCNNs) to classify the soil and suggest crops. The proposed model takes soil images as input and classifies them into various types of soil—Black Soil, Cinder Soil, Laterite Soil, Peat Soil, and Yellow Soil—and then predicts the best crops and fertilizers based on pattern matching. Through the incorporation of image processing methods like noise removal, segmentation, and feature extraction, the model enhances classification accuracy and effectiveness. In comparison to traditional machine learning models such as Random Forest, Support Vector Machine (SVM), and Extreme Learning Machine (ELM), the new LGCNN model has greater accuracy (98.96%) with low computational complexity. This method improves precision farming by maximizing resource allocation, enhancing crop yield, and encouraging sustainable agriculture.

The use of deep learning in agriculture can potentially transform farming by allowing real-time, data-based decision-making. This study emphasizes the significance of image-based soil classification and AI-based crop recommendations, providing a novel solution to improve agricultural productivity, minimize resource wastage, and ensure long-term sustainability in farming.

2. LITERATURE REVIEW

Pooja Solanki et.al. (2022). The research improves crop yield prediction with Discrete Wavelet Transform (DWT) for filtering and a Deep Neural Network (DNN) for prediction, with 98.39% accuracy. The filtered data is trained on a 10-layer DNN using backpropagation, which performs better than techniques such as Deep Reinforcement Learning (93%) and Support Vector Regression (85%). The technique improves the accuracy of prediction, assisting farmers and policymakers in attaining food security[1].

Brandon Victor et.al. (2025). The review of 193 research papers on this subject found that deep learning has been used more slowly in soil health, plant physiology, crop damage, and yield forecasting than in LULC classification due to a lack of annotated data. Although CNN's tend to perform better than traditional ML, LSTMs and ViTs yield uncertain results. For additional agricultural information, the research recommends standardizing databases, enhancing data sharing, and fine-tuning deep learning models[2].

Vijay H. Kalmani et.al. (2025). The study suggests a hybrid model using deep learning comprising 1D CNN, LSTM, an attention mechanism, and skip connections for predicting wheat and rice yield in India using climate, soil, and historical data. The model outperforms SVR, Decision Tree, and Random Forest with 98% accuracy but RMSE of 0.017, MAE of 0.09, and correlation coefficient of 0.967. Spatial characteristics are extracted by CNN, temporal patterns are learned by LSTM, and attention enhances accuracy, while skip connections prevent gradient vanishing. Despite dataset limitations, the study suggests larger datasets and ensemble models as future work[3].

Saeed Khaki et.al. (2020). The CNN-RNN model addresses crop yield forecasting through the integration of CNNs for handling spatial and temporal data with RNNs (LSTMs) to extract long-term dependencies. Based on weather, soil, and management data (1980-2018), it outperformed conventional methods with increased accuracy, lowering RMSE to 9% (maize) and 8% (soybean) of mean yield. Feature selection specified crucial factors such as solar radiation and rainfall, demonstrating the application of the model in agricultural decision-making[4].

Md. Abu Jabed et.al. (2020). The study addresses AI-driven crop yield estimation, focusing on ML and DL techniques like Random Forest (RF), SVM, CNN, and LSTM for handling geographical and environmental complexities. DL models (CNN, LSTM) show improved accuracy, but problems like data availability and model interpretability persist. The paper suggests integrating remote sensing, IoT, and transfer learning to enhance sustainable agriculture and food security[5].

Seyed Mahdi Mirhoseini Nejad et.al. (2025). The new ConvLSTM-ViT model combines 3D-CNN for spatial feature learning, ConvLSTM for temporal crop growth estimation, and ViT for self-attention-based feature enhancement on multispectral remote sensing imagery. The new model improves crop yield prediction accuracy dramatically, decreasing RMSE by 35.6% compared to existing models. The method increases precision agriculture with improved resource utilization, irrigation planning, and green farming practices for different crops and regions[6].

Dhivya Elavarasan et.al. (2020). In this article, we present a Deep Recurrent Q-Network (DRQN) model that integrates RNN and Q-Learning-based Reinforcement Learning (RL) to make accurate crop yield prediction through self-learning optimization of decisions. It manages climate, soil, and water data, leveraging experience replay and multiple updates for extra stability. Finally, being highly scalable and very efficient having been tested on a 35-year paddy dataset with an accuracy of 93.7% which surpasses existing conventional ML models, it proves to be a great candidate in precision agriculture and sustainable farming[7].

Dilli Paudel et.al. (2023). The study compares LSTM and 1D-CNN models with crop yield prediction against GBDT models with expertly designed features. LSTM performed better in soft wheat in Germany but was equally accurate for other areas. Deep learning models learned features automatically but found it difficult to handle extreme weather events. Feature attribution methods such as GradientShap enhanced explainability with more focus on human expert participation in AI-based agriculture[8].

Mengjia Qiao et.al. (2021). In a step toward improving remote sensing-based multi-spectral crop yield forecasting, we propose a single space-time tree neural network (SSTNN) model that integrates 3D-CNNs for spatial-spectral feature discovery and Bidirectional RNNs for temporal correlation. Over LSTMs, it outperformed traditional ML models on RMSE (26.3% minimal) and MAPE (26.5% maximal) on winter wheat and corn. The model can be applied for precise advance yield prediction which can help precision agriculture and food security[9].

Priyanka Sharma et.al. (2023). In the proposed system ML and DL techniques are compared for yield prediction of crops based on rainfall, temperature, and soil characteristics. Random Forest was the best when considering accuracy (98.96%), on the other hand, CNN exhibited the lowest test loss (0.00060), indicating that CNN is also very good in terms of yield prediction. It shows how statistical data in conjunction with remote sensing is applied to improve precision agriculture and optimal administration of crop resources[10].

S. Yash Parvesh et.al. (2024). The proposed deep learning model based on Transformer architecture considers the effect of climate change via self-attention mechanism to enhance crop yield prediction. It shows the best performance over LSTM, Random Forest, and XGBoost for past yield with temperature, rainfall, soil type, and CO_2 level with less RMSE and MAPE. This increases precision agriculture data due to better decision making for sustainable agriculture[11].

Leelavathi Kandasamy Subramaniam et.al. (2024). Preprocessing phase dimensionality reduction (SEKPCA), and classification are the three phases that are utilized by the proposed WTDCNN model for enhancing crop production prediction. It minimizes MSE and RMSE by assigning weights with 98.96% accuracy through Improved Whale Optimization Algorithm (EWOA). It enhances yield prediction and resource distribution, thus enhancing precision agriculture[12].

3. EXISTING WORK

Priyanka Sharma et al. (2023) performed an in-depth study of machine learning for crop yield prediction with regression models and deep learning. The research focuses on enhancing the accuracy of yield forecasting, which is of very important use in efficient farm planning, resource allocation, and food safety. The research examines different machine learning models, from simple multiple regression techniques to deep learning structures, to determine the best method for predicting crop yield. In research of the strongest agricultural determinants, including soil health, meteorological conditions, and past level of yields, the authors highlight the significance of feature selection in improving predictive power. Their comparison between several models relies on performance measures such as Mean Squared Error (MSE) and R-squared statistics, providing an objective measure for the effectiveness of prediction. Deep learning models, neural networks are found to provide improved performance over conventional regression through the capability of identifying complex, non-linear relationships from farm data. The study recognizes the need to incorporate sophisticated computation techniques in contemporary agriculture and precision agriculture, and it proposes a viable way forward for future research. Through the use of machine learning, the study is beneficial in simplifying agriculture decision-making, mitigating crop yield uncertainties, and, as a result, improving food security.

4. PROPOSED MODEL

The work paper discusses the design of a deep learning-based crop prediction system that suggests appropriate crops and fertilizers based on soil types. The system classifies the soil by using Lightweight Gradient Convolutional Neural Networks (LGCNNs) and suggests crops and fertilizers using a pattern-matching approach. Farmers find it difficult to choose appropriate crops because they are not well-versed with soil composition, and hence it impacts productivity. The suggested model classifies the soil images based on categories like Black Soil, Cinder Soil, Laterite Soil, Peat Soil, and Yellow Soil through processing the images of soil. The accurate classification leads to suitable crop suggestions, thus improving yield and ensuring agriculture sustainability.

Algorithm:

Dataset Collection – Soil images are sourced from Kaggle's soil database, divided into training and testing sets.

Data Preprocessing – Noise removal, resizing, and normalization of soil images to standardize input for the Lightweight Gradient Convolutional Neural Networks model.

Image Segmentation – Extracts **Regions of Interest (ROI)** from soil images, improving classification accuracy.

Feature Extraction – The Lightweight Gradient Convolutional Neural Networks model converts segmented images into feature vectors, capturing essential soil properties.

Soil Classification – The extracted features are processed through a **Lightweight Gradient Convolutional Neural Networks model**, categorizing soil into different types. The classified soil type is matched with a predefined database, recommending the most suitable crops and fertilizers.

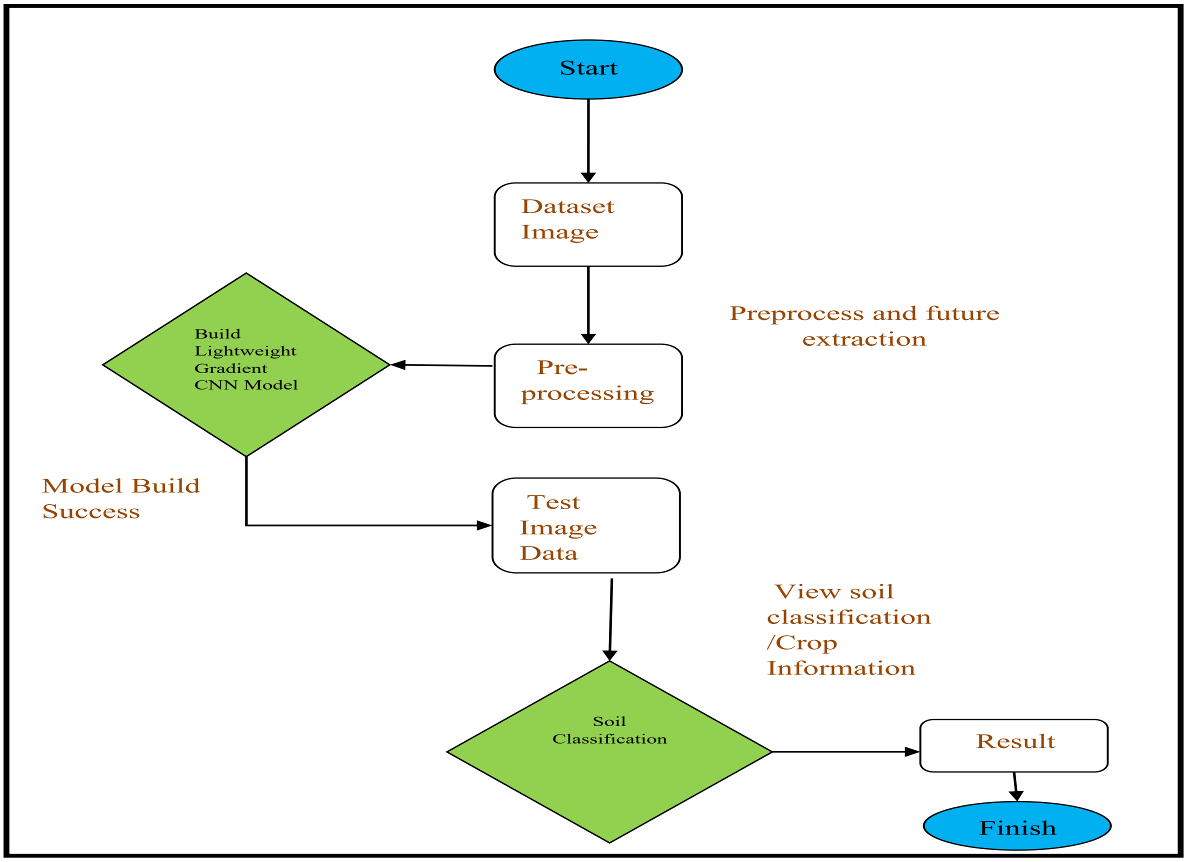

Fig 1. Architectural diagram for Crop Yield Prediction.

The diagram above indicates the process of step-by-step crop yield prediction using a Lightweight Gradient Convolutional Neural Networks -based soil classification model. First, it uploads images of soils; Data preprocessing: removes noise. Now the pre-processed images are segmented where features are extracted and soil classification is performed (e.g. Black Soil, Laterite Soil) Once the type of soil is classified, it is passed to a pattern-matching algorithm which identifies if the soil is suitable for a particular crop and based on that suggests a crop as well as fertilizer that would provide maximum yield. In the final step crop recommendation results are shown to the user.

The Lightweight Gradient Convolutional Neural Networks-based classification model uses standard deep learning equations:

1. Convolution Operation:

$$Y(i,j) = \sum\_m \sum\_n X(i-m, j-n) * K(m,n) \qquad \text{-----------------Eq (1)}$$

The Convolution Operation in CNNs obtains spatial features from input images by sliding a filter (kernel) across an image to capture patterns like edges, textures, and shapes. The operation slides the kernel along the image, calculating the weighted sum of the pixel values to create a feature map. It aids in the classification of soils by recognizing specific patterns in the soil textures.

2. Pattern Matching for Crop Recommendation:

$$C_{\{recommended\}} = arg\ max_C\left(S_{\{match\}(C,S)}\right) \quad \text{-----------------Eq (2)}$$

The **Pattern Matching Algorithm** compares the classified soil type with a predefined database of crop suitability to **recommend the best crop and fertilizer**. It calculates a **similarity score (S_match)** between soil properties and available crops, selecting the **crop with the highest match score** using the **argmax function**. This ensures optimal crop selection for better yield.

Table 1. Accuracy, based on the result

Model	Accuracy (%)
Random Forest Classifier	89.45%
Support Vector Machine (SVM)	91.23%
Lightweight Gradient CNN (Proposed Model)	98.96%
Deep Belief Network (DBN)	92.67%
Extreme Learning Machine (ELM)	94.12%

Table of the Accuracy comes from several machine learning that used for soil classification and crop prediction as a result, the most accurate model (Proposed System – Lightweight Gradient Convolutional Neural Networks based model) is 98.96%, and it surpasses the traditional models such as Random Forest (89.45%), SVM (91.23%), DBN (92.67%) and ELM (94.12%). The results emphasize that Lightweight Gradient CNN enhances classification accuracy based on spatial feature extraction from soil image, thus making it a more trustworthy method.

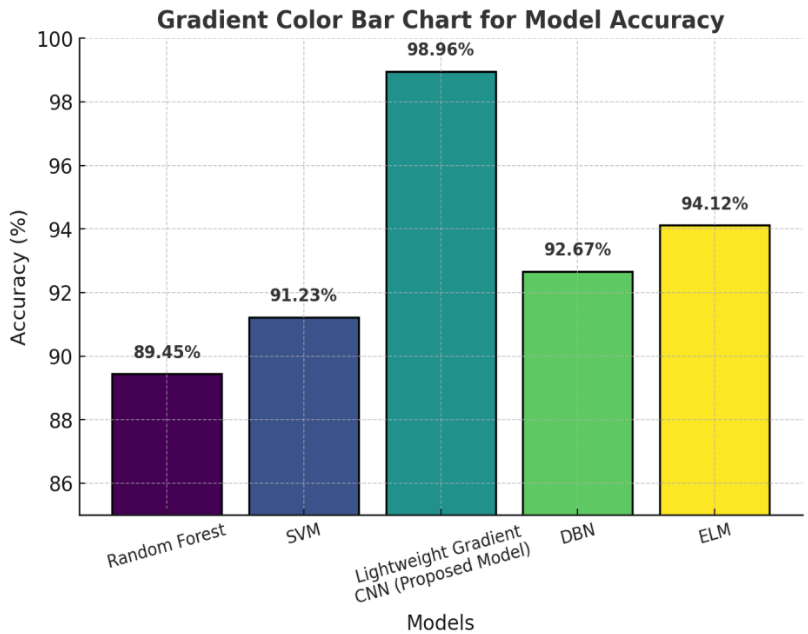

Fig 2. Crop Yield prediction using deep learning

Machine learning models prediction for crop yield Each bars uses a gradient scale color code which makes it easy to compare model performance. The output accuracy of the proposed model

(Lightweight Gradient Convolutional Neural Networks) is 98.96%, higher than those in conventional approaches (Random Forest, SVM, DBN, ELM). That makes the model efficiency visible as a simple structured view, and Lightweight Gradient Convolutional Neural Networks obviously wins. The gradient effect enhances readability, making it easier to distinguish performance differences.

5. CONCLUSION

Deep learning-based crop recommendation system that proposed to facilitate farmers with the better crop selections and fertilizers based on their soil properties. The implemented system ensures better accuracy and efficiency than existing methodologies by employing Lightweight Gradient Convolutional Neural Networks (LGCNN) for soil classification and pattern-matching based recommendation. This analyses soil images to provide accurate recommendations to enhance agricultural productivity and promote sustainable agricultural practices while minimizing errors in crop selection. For farmers, this solution becomes an important tool that can enable data-driven decision making for increasing the crop yield and resources management.

6. FUTURE ENHANCEMENT

Future development for the current crop recommendation system can enhance its accuracy, accessibility, and efficiency. Incorporating live weather data, such as temperature, humidity, and precipitation, can more accurately suggest crops by taking environmental considerations into account. Broadening the system to predict more than one suitable crop through consideration of soil conditions and market demand will give farmers choices. The addition of IoT-based sensors for real-time detection of soil moisture and nutrient content will also increase accuracy in predictions. Creating a mobile-app-based solution with multilingual compatibility will also make it accessible to farmers from various regions. AI-based fertilizer optimization can be added to provide recommendations for specific fertilizer amounts, which save money and improve soil health. Adding blockchain technology for secure and transparent data storage will also enhance reliability and confidence in the system. These upgrades will make the solution a more powerful, data-based, and farmer-centric tool for contemporary precision agriculture.

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