



Crop Recommendation System for Farmers Using Convolutional Neural Network

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Abstract: Agriculture plays an important role in food security and the economic development of many countries. Selecting the most suitable crop for a particular field is a major challenge for farmers because crop growth depends on soil properties, nutrients, temperature, humidity, rainfall, pH, and climatic conditions. Traditional crop selection mainly depends on farmers experience and local knowledge, which may not always provide accurate recommendations under changing environmental conditions. Artificial Intelligence (AI), Machine Learning (ML), and Deep Learning (DL) provide effective solutions for data-driven agricultural decision making. This paper presents a review of crop recommendation systems with particular emphasis on **Convolutional Neural Networks (CNNs)**. CNNs can automatically learn useful patterns from soil images, remote-sensing images, and other agricultural data, while CNN-based hybrid models can also be combined with environmental and soil parameters. Recent studies have explored Random Forest, XGBoost, Support Vector Machine, LSTM, CNN, attention-based networks, Transformer models, and hybrid deep-learning architectures for crop recommendation. This review examines research published from 2020 to 2026, summarizes their datasets, preprocessing methods, algorithms, and major findings, and identifies research gaps related to dataset availability, regional generalization, explainability, multimodal data integration, and real-time deployment. A CNN-based crop recommendation system can potentially provide farmers with localized and intelligent recommendations while reducing inappropriate crop selection, improving productivity, and supporting sustainable farming.

Keywords: Crop Recommendation, Convolutional Neural Network, CNN, Deep Learning, Precision Agriculture, Smart Farming, Soil Classification, Machine Learning, Farmers, Agriculture.

1. INTRODUCTION

Agriculture is an important sector for global food production and rural employment. Selecting a suitable crop directly affects farm productivity, income, and resource utilization. Crop suitability depends on factors such as soil nutrients, pH, temperature, rainfall, humidity, water availability, and seasonal conditions.

Traditionally, farmers select crops based on personal experience, local knowledge, historical practices, and expert advice. However, these methods may become less reliable due to Climate variability, soil degradation, irregular rainfall, and changing temperatures.

The availability of agricultural datasets has enabled the use of Artificial Intelligence and Machine Learning for automated crop recommendation. Various machine learning algorithms have been used to identify suitable crops from soil and environmental parameters. Deep Learning techniques such as Convolutional Neural Networks (CNNs) can learn complex patterns from agricultural data and can also be combined with other models for improved analysis. Therefore, a CNN-based crop recommendation system can act as an intelligent decision-support system by analyzing agricultural parameters and recommending a suitable crop.

II. LITERATURE SURVEY

Crop recommendation has become an important research area in **Artificial Intelligence (AI)-enabled smart agriculture**. Recent advances in Machine Learning (ML), Deep Learning (DL), Convolutional Neural Networks (CNN), Internet of Things (IoT), remote sensing, Explainable Artificial Intelligence (XAI), and precision agriculture have significantly improved intelligent crop selection systems. Researchers have proposed various models using **soil properties, NPK values, soil pH, temperature, humidity, rainfall, soil images, satellite data, and sensor information**. Traditional machine learning algorithms such as Random Forest, Support Vector Machine, Decision Tree, and XGBoost have shown good performance on structured agricultural datasets. Recent studies have also explored CNN, LSTM, hybrid deep learning, Vision Transformer, and explainable AI models for automatic feature



extraction and crop recommendation. These developments indicate a shift toward intelligent, data-driven, and farmer-oriented agricultural decision-support systems.

Van Klompenburg et al. (2020) conducted a systematic review of machine learning techniques used in crop prediction and agricultural applications. The study analyzed different machine learning and deep learning approaches using factors such as soil properties, temperature, rainfall, and other environmental conditions. CNN, LSTM, and neural network models were identified as promising techniques for learning complex agricultural patterns. The review highlighted that deep learning can reduce the need for manual feature extraction and improve prediction performance when sufficient training data are available. However, the study mainly focused on crop yield prediction rather than direct crop recommendation, and challenges related to dataset size and generalization were identified.

Inference: Deep learning and CNN techniques have strong potential for agricultural prediction and decision-support applications.

Ponnusamy et al. (2021) investigated machine learning approaches for crop recommendation using agricultural and environmental parameters. The study considered factors such as soil moisture, temperature, and other field conditions to identify suitable crops. Different machine learning algorithms were evaluated to establish relationships between agricultural conditions and crop suitability. The results demonstrated that machine learning can assist farmers in selecting appropriate crops based on field conditions. However, the approach mainly used structured numerical data and provided limited attention to image-based soil analysis.

Inference: Machine learning can support automated crop selection using soil and environmental information.

Shingade (2022) proposed a hybrid deep learning approach for crop prediction and recommendation under changing environmental conditions. The model considered parameters such as temperature, humidity, rainfall, and soil pH. Deep learning was used to learn the relationship between environmental factors and suitable crops. The study demonstrated that deep learning models can handle nonlinear relationships in agricultural data. However, the system mainly relied on numerical environmental parameters and did not extensively use soil images.

Inference: Deep learning can effectively model complex relationships between environmental conditions and crop suitability.

Meedeniya et al. (2022) developed a crop recommendation system using remote sensing and soil-related information for Rajasthan, India. Landsat-8 satellite data were used to obtain soil characteristics, and optimization techniques were applied to identify suitable crops. The study demonstrated that remote sensing can provide valuable information for location-specific crop recommendation. However, the approach depends mainly on satellite data and may not capture detailed field-level soil characteristics.

Inference: Remote sensing and satellite information can improve location-specific crop recommendation.

Shingade and Mudhalwadkar (2023) developed a sensor information-based crop recommendation system for fertile regions of Maharashtra. The system used soil and environmental sensor information to recommend suitable crops. The study demonstrated the usefulness of real-time agricultural data for precision farming and automated crop selection. However, the system mainly relied on numerical sensor information and did not incorporate soil-image analysis using CNN.

Inference: IoT-based soil and environmental sensors can provide useful real-time information for crop recommendation.

Rani et al. (2023) proposed a machine-learning-based optimal crop selection system for smart agriculture. The study analyzed environmental and agricultural parameters and applied machine learning techniques to identify suitable crops. The research demonstrated that environmental conditions have an important influence on crop selection. However, the system primarily used structured agricultural data and had limited integration of visual soil information.

Inference: Environmental and agricultural parameters are important for developing accurate crop recommendation systems.

Shams et al. (2024) proposed an explainable crop recommendation approach called **XAI-CROP**. The study evaluated machine learning algorithms including Gradient Boosting, Decision Tree, Random Forest, and Naïve Bayes for crop recommendation. Explainable AI techniques were incorporated to identify the factors influencing the recommendations. The study emphasized that interpretability is important because farmers and agricultural experts need to understand why a particular crop is recommended. However, the system mainly considered tabular agricultural data rather than soil images.

Inference: Explainable AI can improve farmer confidence and understanding of crop recommendation systems.



Dey et al. (2024) investigated machine-learning-based crop recommendation using **nitrogen, phosphorus, potassium, soil pH, temperature, rainfall, and humidity**. Several algorithms, including Support Vector Machine, Random Forest, XGBoost, KNN, and Decision Tree, were evaluated. The results showed that combining soil nutrients with climatic parameters can effectively identify suitable crops. However, the system did not extensively use image-based soil features, which could provide additional information about soil characteristics.

Inference: Combining soil nutrients and climatic conditions provides an effective basis for crop recommendation.

Choudhury et al. (2024) developed a crop recommendation and forecasting system using historical agricultural and weather data from Maharashtra. Machine learning and deep learning approaches, including LSTM, were used to analyze historical patterns and support crop selection. The study demonstrated the importance of historical weather and regional agricultural information in crop recommendation. However, the approach mainly focused on numerical and temporal data and did not incorporate CNN-based soil-image features.

Inference: Historical weather and regional agricultural data can improve location-specific crop recommendation.

Shastri et al. (2025) developed a crop recommendation system using supervised machine learning and explainable artificial intelligence. Soil, weather, and agricultural parameters were used to identify suitable crops. The study emphasized the importance of explainability in agricultural AI systems so that users can understand the factors influencing the recommendation. However, the work mainly focused on structured data rather than visual soil characteristics.

Inference: Combining machine learning with explainable AI can make crop recommendation systems more transparent and reliable.

Venkateswara and Padmanaban (2025) proposed an interpretable deep learning model for crop and fertilizer recommendation. The study used soil and environmental parameters and applied TabNet with SHAP-based explanations. The model demonstrated high prediction performance while identifying important input features influencing crop recommendations. However, the system mainly focused on numerical agricultural information and did not extensively analyze soil images using CNN.

Inference: Interpretable deep learning can provide accurate and understandable crop and fertilizer recommendations.

A CNN and Vision Transformer-based study (2025) proposed an advanced framework combining **Convolutional Neural Networks (CNN) and Vision Transformers (ViT)** for soil classification followed by crop recommendation. Soil images were augmented and used to train deep learning models, while soil type, nutrients, pH, and climatic conditions were considered for crop recommendation. The study is particularly relevant to CNN-based crop recommendation because CNN automatically extracts visual soil features that are difficult to obtain from numerical parameters alone. However, the combined deep learning architecture requires considerable computational resources.

Inference: CNN-based soil-image analysis combined with agricultural parameters can provide a promising approach for intelligent crop recommendation.

Tripathy et al. (2026) investigated nonlinear deep learning models for intelligent crop recommendation in precision agriculture. The study considered models such as **ANN, CNN, RNN, LSTM, and CRNN** for analyzing soil and climatic characteristics. Ensemble strategies were also investigated to improve crop recommendation performance. The study demonstrated that deep learning models can capture complex nonlinear relationships between agricultural parameters and crop suitability. However, these models require sufficient training data and computational resources for effective implementation.

Inference: CNN and other deep learning models can effectively capture nonlinear agricultural relationships and improve crop recommendation.

Hybrid deep learning research (2026) investigated automated soil classification and crop recommendation using deep learning techniques. The approach focused on extracting useful information from soil images and combining it with agricultural parameters for crop suitability prediction. The study demonstrated the potential of image-based deep learning for supporting agricultural decision-making. However, large-scale field validation and adaptation to different geographic regions are still required.

Inference: Automated soil-image analysis using deep learning is a promising direction for developing practical crop recommendation systems.



Author & Year	Dataset / Data	Preprocessing / Features	Method	Main Contribution	Limitation
Jain et al. (2020)	Digital document and identity datasets	Image enhancement, OCR, text extraction	CNN, OCR	Automated document authentication	Limited document types
Raja et al. (2021)	Identity and scanned document images	Noise removal, resizing, feature extraction	CNN-based classification	Detection of forged documents	Requires large image datasets
Kumar et al. (2021)	Government and identity documents	OCR, image preprocessing, text matching	OCR + Machine Learning	Automated information extraction and verification	OCR errors in low-quality documents
Sharma et al. (2022)	Scanned certificates and ID documents	Image enhancement, segmentation, feature extraction	CNN + OCR	Document classification and authenticity checking	Performance affected by image quality
Patel et al. (2022)	Academic certificates	Text extraction, layout analysis	Deep Learning + OCR	Automated certificate verification	Limited to selected certificate formats
Singh et al. (2023)	Identity document datasets	Face detection, image preprocessing	CNN + Face Recognition	Links identity with submitted documents	Privacy and biometric concerns
Kumar & Sharma (2023)	Digital certificates and institutional records	Hash generation, metadata extraction	Blockchain + Cryptography	Tamper-resistant document verification	Blockchain infrastructure required
Das et al. (2023)	Scanned and digitally generated documents	OCR, text normalization, feature extraction	Machine Learning	Fraud and tampering detection	Difficulty detecting sophisticated alterations
Ahmed et al. (2024)	Document images and forged samples	Image enhancement, segmentation, augmentation	CNN + Transfer Learning	Improved detection of manipulated documents	Requires computational resources
Reddy et al. (2024)	Digital certificates and identity documents	OCR, metadata and hash analysis	Blockchain + AI	Secure and automated verification	Integration complexity
Sharma et al. (2024)	Multi-format document datasets	Layout detection, OCR, feature extraction	YOLO + OCR	Detects document regions and extracts information	Sensitive to document layout variations
Gupta et al. (2025)	Authentic and forged document images	Data augmentation, image normalization	CNN + Vision Transformer	Improved document forgery detection	High computational requirements
Patil et al. (2025)	Academic and professional certificates	OCR, QR extraction, metadata validation	AI + QR/Blockchain	Multi-level document authentication	Requires standardized digital records
Kumar et al. (2025)	Identity and educational documents	OCR, face matching, feature extraction	Deep Learning + Biometrics	Combines document and identity verification	Privacy and security challenges
Digital	Digital	OCR, image	AI +	Integrated secure	Scalability and



Author & Year	Dataset / Data	Preprocessing / Features	Method	Main Contribution	Limitation
Document Verification Study (2026)	documents, certificates and identity records	preprocessing, metadata and authenticity features	Cryptography + Blockchain	digital document verification system	interoperability challenges

III. RESEARCH GAP

Although several machine learning and deep learning models have been developed for crop recommendation, some research gaps remain. Most studies use limited soil and environmental parameters and may not generalize well across different regions, soil types, and seasons. Many studies also focus mainly on accuracy while giving less attention to interpretability, robustness, and practical usability.

Another gap is the limited use of multimodal agricultural data such as soil images, satellite images, IoT sensor data, weather information, and historical records. Combining CNN-based image features with numerical soil and climatic parameters could improve crop recommendation. However, the availability of sufficient and diverse labeled soil-image datasets remains a challenge. Techniques such as data augmentation and transfer learning can help address this limitation.

Explainable Artificial Intelligence (XAI) is also an important research gap. Many deep learning models, including CNNs, operate as black-box systems, making it difficult for farmers to understand why a particular crop has been recommended. Providing explanations based on soil characteristics, climatic conditions, and important image regions can increase farmer confidence and improve the practical acceptance of AI-based recommendation systems.

Privacy and security issues are also becoming important with the increasing use of IoT and cloud-based agricultural systems. Farmers may generate large amounts of field and sensor data through smart farming devices. Although privacy-preserving techniques such as federated learning can reduce the need to share raw data, their application to crop recommendation systems is still limited.

Another research gap involves the **lack of external and real-field validation**. Many existing systems are evaluated using benchmark datasets collected under controlled or limited conditions. Their performance may decrease when applied to actual farms because of differences in soil, weather, crop varieties, irrigation practices, and regional agricultural conditions. Therefore, large-scale field testing across different regions is required.

Finally, relatively few studies have developed lightweight and real-time crop recommendation systems that integrate **CNN, IoT sensors, mobile applications, edge computing, and cloud platforms**. Therefore, future research should focus on developing intelligent, explainable, region-specific, and computationally efficient crop recommendation systems that combine **soil images with NPK, pH, temperature, humidity, rainfall, and other agricultural parameters**.

IV. CHALLENGING ISSUES

Several challenges affect the practical implementation of CNN-based crop recommendation systems:

- **Limited and Poor-Quality Data:** Agricultural datasets may have fewer samples, missing values, noise, or limited soil-image data, which can reduce model accuracy and generalization.
- **Regional Variation:** Soil, climate, crop varieties, and farming practices differ across regions, making it difficult for one model to work equally well everywhere.
- **Class Imbalance:** Unequal numbers of samples for different crops may cause the model to favor frequently represented crops.
- **Soil Image Quality:** Lighting, moisture, background, and image resolution can affect CNN performance.
- **Feature Integration:** Combining image features with NPK, pH, temperature, humidity, and rainfall requires effective feature selection and fusion.
- **Interpretability and Complexity:** CNN models can be difficult to interpret and advanced models may require high computational resources.
- **Real-Time and Climate Changes:** Sensor connectivity, changing weather, and seasonal conditions can affect recommendation reliability.
- **Farmer Adoption and Validation:** Simple user interfaces, local-language support, and testing on real farms are necessary for practical adoption.



V. MOTIVATION

Farmers must select crops before the cultivation season, but inappropriate crop selection can result in reduced productivity, financial loss, and inefficient use of water and fertilizers. Climate variability further increases this uncertainty.

A CNN-based crop recommendation system can provide farmers with data-driven recommendations instead of relying only on traditional experience. CNNs are particularly useful when soil or agricultural images are available because they can automatically extract important visual characteristics.

The proposed system can therefore combine **CNN-based image analysis with soil and climatic parameters** to recommend suitable crops for a specific field. Such a system can support farmers in making faster and more informed decisions.

VI. SCOPE OF THE STUDY

The scope of crop recommendation research has expanded considerably with the integration of artificial intelligence into agriculture. This study focuses on recent developments in **machine learning, deep learning, Convolutional Neural Networks (CNN), Internet of Things (IoT), remote sensing, explainable AI, and precision agriculture** for intelligent crop recommendation. The study covers various prediction techniques, including Decision Trees, Random Forest, Support Vector Machine, K-Nearest Neighbor, Naïve Bayes, XGBoost, Artificial Neural Networks, Convolutional Neural Networks, Long Short-Term Memory networks, Transformer models, ensemble learning, and hybrid intelligent systems.

It also considers commonly used agricultural datasets, soil images, NPK values, soil pH, temperature, humidity, rainfall, preprocessing methods, feature extraction techniques, and performance evaluation metrics. Furthermore, the study highlights emerging technologies such as **IoT-based soil monitoring, satellite imagery, remote sensing, cloud computing, edge computing, multimodal learning, and explainable AI**. The findings of this study provide useful guidance for researchers, farmers, agricultural organizations, and policymakers in developing next-generation intelligent crop recommendation systems.

VII. APPLICATIONS OF CROP RECOMMENDATION SYSTEM

Artificial intelligence-based crop recommendation systems have numerous applications in modern agriculture.

1. **Crop Selection:** Machine learning and CNN models assist farmers in identifying the most suitable crop based on soil and environmental conditions.
2. **Precision Agriculture:** AI-based systems support field-specific crop selection using soil, weather, and sensor information.
3. **Soil-Based Recommendation:** CNN models can analyze soil images to identify visual characteristics such as soil type, texture, and appearance.
4. **IoT-Based Smart Farming:** Integration with IoT sensors enables continuous monitoring of soil moisture, temperature, humidity, and other agricultural parameters.
5. **Personalized Farming:** Crop recommendations can be generated according to the specific soil and climatic conditions of an individual farm.
6. **Remote Agricultural Advisory:** Mobile and web-based systems can provide crop recommendations to farmers without requiring continuous access to agricultural experts.
7. **Smart Agriculture:** Integration of AI, IoT, cloud computing, and remote sensing can support automated agricultural decision-making.
8. **Sustainable Farming:** Appropriate crop selection can improve resource utilization and reduce unnecessary consumption of water and fertilizers.
9. **Mobile Agricultural Applications:** Smartphone applications can allow farmers to upload soil images and enter basic field parameters to obtain crop recommendations.
10. **Regional Crop Planning:** Government agencies and agricultural organizations can analyze soil and climate information to identify suitable crops for different geographical regions.



VIII. FUTURE RESEARCH DIRECTIONS

The rapid development of artificial intelligence presents several promising opportunities for improving crop recommendation systems. Future research should focus on the following directions:

1. **Development of Large-Scale Agricultural Datasets:** Future studies should collect large and diverse datasets containing soil images, NPK values, soil pH, weather information, crop history, and geographical information from different agricultural regions. This can improve model robustness and generalization.
2. **Multimodal Data Integration:** Combining **soil images, NPK values, weather data, satellite images, IoT sensor information, and historical crop data** can provide more comprehensive information for crop recommendation.
3. **CNN-Based Soil Image Analysis:** Future systems should investigate advanced CNN architectures for automatically extracting soil texture, color, and other visual characteristics from soil images.
4. **Explainable Artificial Intelligence:** Techniques such as **Grad-CAM, SHAP, LIME, and attention mechanisms** can be incorporated to explain why a particular crop is recommended and improve farmer confidence.
5. **IoT-Based Smart Agriculture:** Future crop recommendation systems should integrate soil moisture sensors, temperature sensors, humidity sensors, and other IoT devices for continuous field monitoring and real-time recommendation.
6. **Edge and Cloud Computing:** Combining edge computing with cloud-based agricultural platforms can reduce processing time and support real-time crop recommendation even in areas with limited connectivity.
7. **Hybrid Artificial Intelligence Models:** Future research should investigate hybrid models combining **CNN, LSTM, Transformer, optimization algorithms, and ensemble learning** to improve prediction accuracy and computational efficiency.
8. **Personalized Crop Recommendation:** AI models should incorporate **soil characteristics, climate, location, irrigation availability, crop history, and seasonal conditions** to provide field-specific crop recommendations.
9. **Climate-Aware Crop Recommendation:** Future systems should consider changing temperature, rainfall patterns, drought conditions, and other climate-related factors when recommending crops.
10. **Lightweight CNN Models:** Lightweight CNN architectures should be developed for deployment on **smartphones, IoT devices, and edge-computing platforms**, making the technology accessible to farmers.
11. **Regional and Local-Language Support:** Crop recommendation applications should be adapted to specific regions and provide recommendations in local languages to improve usability among farmers.
12. **Field Validation and Deployment:** Future research should conduct real-world experiments across different farms, soil types, seasons, and geographical regions to evaluate the practical effectiveness of CNN-based crop recommendation systems.

IX. CONCLUSION

Agriculture is important for food production and economic development. AI, ML, and DL are increasingly used to analyse soil and environmental data for crop recommendation.

Traditional machine learning methods such as Decision Tree, SVM, Random Forest, Naïve Bayes, KNN, and XGBoost have shown useful results on agricultural datasets. Deep learning models such as ANN, CNN, and LSTM can learn complex patterns, while CNNs are useful for soil, satellite, and remote-sensing images.

Recent research also focuses on Explainable AI, IoT, and sensor technologies to improve transparency and provide real-time agricultural information. However, challenges such as limited datasets, regional variation, data imbalance, climate changes, computational requirements, and limited field validation remain.

Overall, a CNN-based crop recommendation system combining soil and environmental parameters such as NPK, pH, temperature, humidity, and rainfall can support suitable crop selection and contribute to smart and sustainable agriculture.

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