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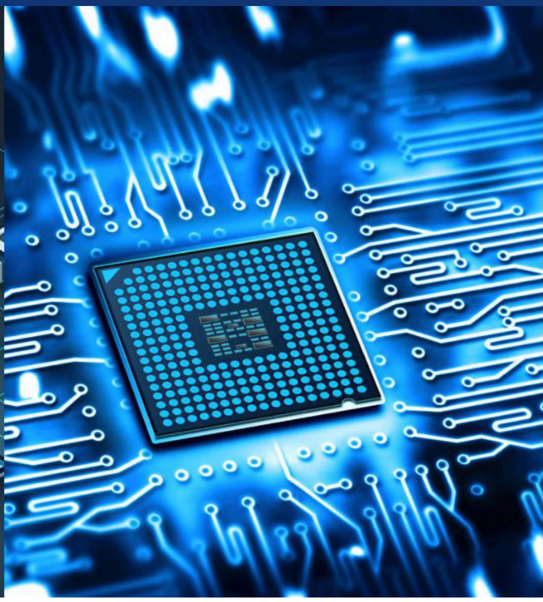

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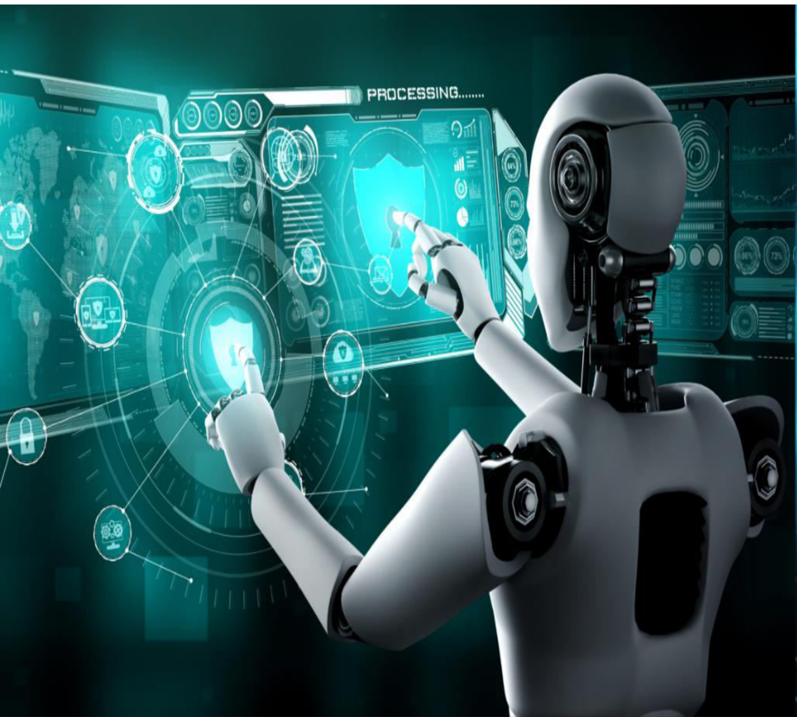

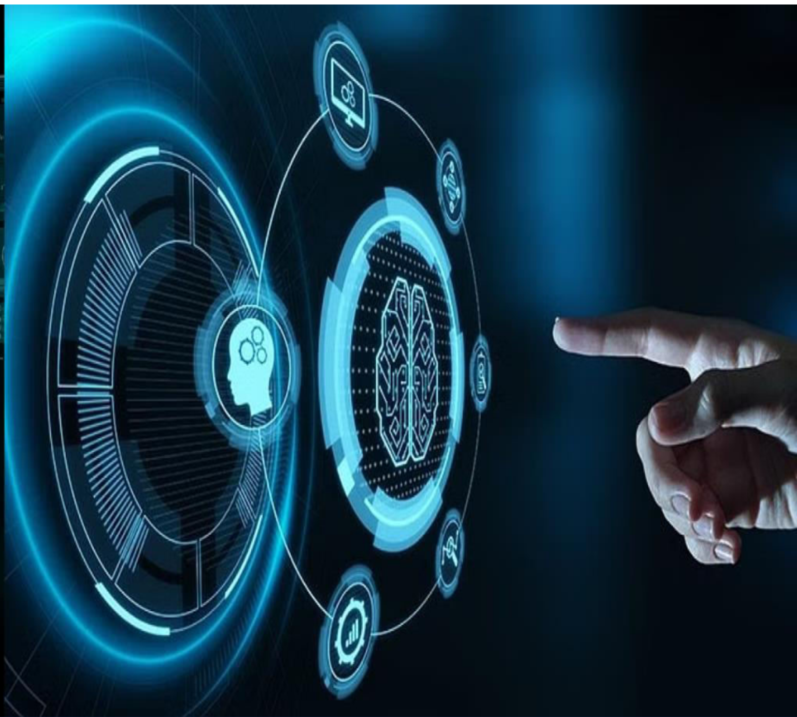

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AI-Based Farmer Query Support and Advisory System

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ABSTRACT: Agriculture remains one of the most essential sectors in developing countries, providing livelihood to millions of farmers and contributing significantly to national food security. However, despite technological advancements in various fields, the agricultural sector still faces critical challenges such as unpredictable weather patterns, pest infestations, improper fertilizer usage, low productivity, and lack of timely expert advice. This paper presents an AI-Based Farmer Query Support and Advisory System designed to bridge the communication gap between farmers and experts by delivering reliable information instantly through mobile devices, chatbots, or web applications. The system takes farmer queries in text or voice form and processes them using CNN techniques to understand intent, then retrieves the most appropriate advisory from a comprehensive agricultural knowledge base. The system tailors responses based on crop type, growth stage, geographical location, and weather conditions. Experimental evaluation on a dataset of 10,000 labeled agricultural queries demonstrates that the CNN-based intent classifier achieves an overall accuracy of 91.4%, with a weighted F1-score of 0.903, outperforming SVM (84.2%) and Naive Bayes (78.6%) baselines. The system responds to queries in 1–3 seconds, confirming its suitability for real-time deployment in rural agricultural advisory scenarios.

KEYWORDS: Artificial Intelligence, Convolutional Neural Network, Farmer Advisory System, Agricultural Chatbot, Crop Management, Machine Learning, Smart Agriculture, Intent Detection, Convolutional Neural Network.

I. INTRODUCTION

Agriculture remains one of the most essential sectors in developing countries, providing livelihood to millions of farmers and contributing significantly to national food security. However, despite technological advancements in various fields, the agricultural sector still faces critical challenges such as unpredictable weather patterns, pest infestations, improper fertilizer usage, low productivity, and lack of timely expert advice. Farmers often rely on traditional practices, local knowledge, or agricultural officers who may not always be immediately available. As a result, the gap between farmers and scientific agricultural information continues to widen, leading to inefficiencies, reduced crop yields, and economic losses.

In recent years, Artificial Intelligence (AI) has emerged as a transformative technology with the potential to revolutionize various industries, including agriculture. AI-powered systems combined with Convolutional Neural Network (CNN), machine learning, and knowledge-based advisory models enable automated understanding and response to user queries. When applied to the farming ecosystem, such systems can act as virtual agricultural assistants, providing farmers with accurate, personalized, and real-time guidance.

The system takes farmer queries in text or voice form and processes them using CNN techniques to understand the intent. It then retrieves the most appropriate advisory from a comprehensive agricultural knowledge base containing crop-specific information, pest and disease data, fertilizer recommendations, and best farming practices. The system further tailors the response based on factors like crop type, growth stage, geographical location, and weather conditions, ensuring context-aware and practical recommendations.

II. RELATED WORK

Recent advancements in artificial intelligence, convolutional neural network (CNN), and smart advisory systems have significantly contributed to the development of intelligent solutions for farmer query support. Existing research

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primarily focuses on three key areas: intent-based classification, knowledge-driven recommendation systems, and real-time advisory delivery platforms.

AI-driven query classification systems have been widely explored to understand farmer intent based on text and voice inputs. Deep learning models, particularly Convolutional Neural Network (CNN) architectures applied to text classification, have demonstrated high accuracy in identifying intent categories including disease detection, fertilizer recommendation, and irrigation scheduling. CNN-based text classifiers use multiple parallel convolutional filters of varying kernel sizes to capture local n-gram features from embedded token sequences, followed by max-pooling and fully connected layers for multi-class classification. Several studies report the use of CNN models achieving over 90% accuracy in agricultural query understanding across regional languages.

In parallel, research in knowledge-based advisory systems and expert recommendation engines has explored the use of machine learning and rule-based hybrid models to guide farmers with personalized agricultural advice. Dynamic advisory models leverage real-time data such as crop type, soil conditions, weather forecasts, and growth stage to generate context-specific recommendations. These approaches aim to minimize expert dependency by directing farmers to accurate scientific advice.

Real-time monitoring and mobile-based agricultural applications have also gained prominence in bridging the information gap between farmers and experts. Several systems provide disease identification, fertilizer dosage recommendations, and user-friendly voice interfaces to enable timely decision-making. Additionally, advancements in post-harvest management systems use AI to monitor crop maturity and quality during storage and transportation, reducing losses across the supply chain.

Despite these advancements, existing solutions often operate in isolation, focusing either on query understanding, knowledge retrieval, or advisory delivery independently. The proposed system addresses this gap by integrating CNN-driven intent detection, a structured agricultural knowledge base, and intelligent advisory generation into a unified platform.

III. PROPOSED ALGORITHM

The proposed AI-Based Farmer Query Support and Advisory System is designed to intelligently handle farmer queries using convolutional neural network (CNN), machine learning, and smart advisory strategies. The system integrates voice and text input processing, deep learning-based intent detection, knowledge base retrieval, and automated decision-making to provide accurate and timely agricultural guidance.

The algorithm is divided into multiple modules including query acquisition, CNN preprocessing, intent detection, knowledge base lookup, advisory generation, and cloud-based data management. These modules work together to provide real-time monitoring and efficient advisory delivery to farmers.

3.1 Query Acquisition and Input Handling

The first stage of the system involves capturing farmer queries through a mobile or web interface. The captured query is preprocessed before being passed to the CNN and machine learning model.
The preprocessing stage includes:
• Converting voice input to text using speech-to-text APIs
• Normalizing and tokenizing the input text
• Removing noise, stop words, and performing stemming or lemmatization
The processed query is then converted into vector representations suitable for CNN model inference.

$$Qp = Normalize(Tokenize(Q, language))$$

Where:
Q = raw farmer input query
Qp = preprocessed query
This step ensures uniformity and consistency across all input queries regardless of language or input format.

Fig. 3.1.1. Query Acquisition and CNN-Based Intent Detection Workflow

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3.2 CNN-Based Intent and Entity Detection

After preprocessing, the query is passed to a trained Convolutional Neural Network (CNN) model designed for text classification. The input tokens are first converted into dense vector representations using a pre-trained embedding layer (Word2Vec or GloVe). Multiple parallel Conv1D layers with filter sizes of 2, 3, and 4 are then applied to capture local n-gram patterns. ReLU activation is applied after each convolution, followed by Global Max Pooling to extract the most dominant features from each filter. A Dropout layer (rate = 0.5) is applied for regularization, and a fully connected Dense layer with Softmax activation produces the final intent probability distribution.

The output is a probability vector indicating the likelihood of each intent class:

- Disease Identification
- Fertilizer Recommendation
- Irrigation Schedule
- Weather Advisory
- Crop Selection

$$I = \arg\max(Softmax(Dense(GlobalMaxPool(ReLU(Conv1D(Embed(Qp)))))))$$

Where:

CNN_Model = trained CNN text classification model (Embedding → Conv1D → ReLU → MaxPool → Dropout → Softmax)

I = predicted farmer intent

The model also extracts key entities such as crop name, location, growth stage, and symptoms to enable context-aware advisory generation.

3.3 Environmental and Contextual Analysis

To enhance decision-making, the system integrates environmental and contextual data to estimate advisory relevance based on current farming conditions. The parameters considered include temperature and humidity from weather APIs, soil type and moisture level from sensor data, and crop growth stage from the regional farming calendar.

$$R = f(T, H, S, G)$$

Where:

T = temperature

H = humidity

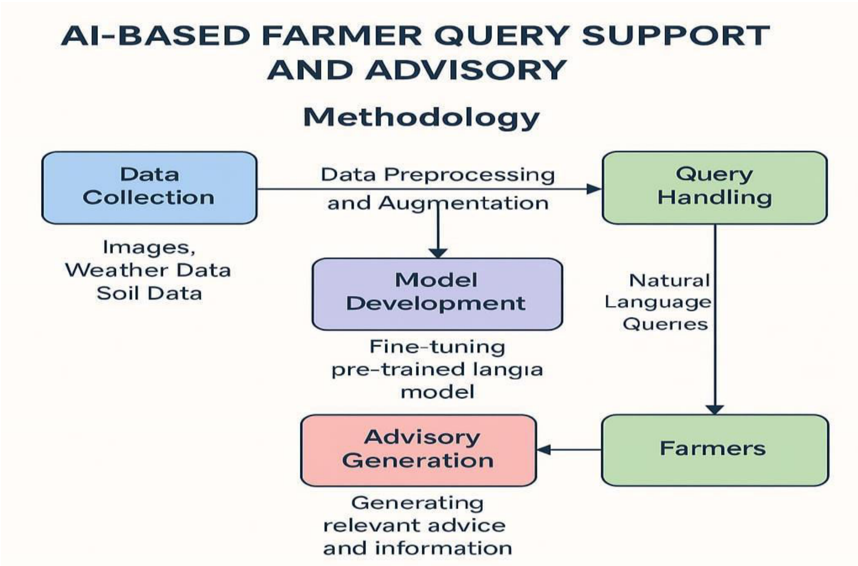
S = soil type

G = crop growth stage

R = contextual relevance score

This module enables proactive identification of advisory that is most relevant to the farmer's current field conditions.

Fig. 3.3.1. AI-Based Farmer Advisory System Architecture for Intelligent Query Handling



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3.4 AI-Based Decision and Advisory Routing Mechanism

Based on the detected intent and contextual analysis, the system determines the optimal advisory action using a rule-based decision engine combined with knowledge base lookup.

- If intent is Disease Identification → Retrieve disease symptoms and treatment recommendations
- If intent is Fertilizer Recommendation and growth stage is early → Provide base fertilizer schedule
- If intent is Weather Advisory → Fetch real-time weather and generate crop precaution advice

The smart advisory routing system assigns the appropriate knowledge base module by analyzing detected crop name, geographic location, regional farming conditions, and urgency based on pest or disease severity level.

3.5 Cloud Data Management and Dashboard Integration

All system data including query logs, advisory records, user feedback, and performance metrics are stored in a cloud-based database (PostgreSQL/Supabase). The dashboard module provides query classification statistics, advisory accuracy and farmer satisfaction metrics, real-time tracking of active user sessions, and environmental impact and crop yield improvement indicators.

3.6 Pseudocode of Proposed Algorithm

```
Step 1: Initialize system components
   Load CNN model (farmer_advisory_cnn.h5)    // Layers: Embedding → Conv1D → ReLU → MaxPool → Dropout
→ Dense → Softmax
   Initialize knowledge base and APIs
Step 2: Capture farmer query (text / voice)
Step 3: Preprocess query
   Convert voice to text → Tokenize → Normalize → Lemmatize → Embed tokens into dense vectors (Word2Vec /
GloVe)
Step 4: CNN-Based Intent Classification
   EmbeddingMatrix ← Embed(preprocessed_query)    // Convert tokens to 2D embedding matrix
   FeatureMaps ← Conv1D(EmbeddingMatrix, filters=[64,128,256], kernel_sizes=[2,3,4])    // Apply convolutional
filters
   ActivatedMaps ← ReLU(FeatureMaps)    // Apply ReLU activation function
   PooledFeatures ← GlobalMaxPooling(ActivatedMaps)    // Extract dominant features
   DroppedFeatures ← Dropout(PooledFeatures, rate=0.5)    // Regularize to prevent overfitting
   IntentScores ← Softmax(DenseLayer(DroppedFeatures))    // Compute class probabilities
   Intent ← argmax(IntentScores)    // Select highest probability intent class
   Entities ← ExtractEntities(preprocessed_query)    // Extract crop, location, stage, symptoms
Step 5: Collect contextual data (T, H, S, G)
   R ← Score(T, H, S, G)
Step 6: Advisory decision making
   IF Intent = Disease → FetchDiseaseInfo(crop, symptoms)
   ELSE IF Intent = Fertilizer → FetchFertilizerSchedule(crop, stage)
   ELSE IF Intent = Weather → FetchWeatherAdvice(location)
   ELSE → FetchGeneralAdvice(intent, entities)
Step 7: Simplify advisory language for farmer understanding
Step 8: Store query, intent, advisory in database
Step 9: Display output on dashboard / mobile app
```

IV. SIMULATION RESULTS

The AI-Based Farmer Query Support and Advisory System was evaluated through functional testing and user interface validation using the developed web-based prototype. The results demonstrate successful implementation of natural language query handling, smart advisory routing, and stakeholder interaction through an intuitive and responsive interface.

The system demonstrates an integrated farmer advisory workflow that connects query input, intent detection, knowledge base retrieval, advisory generation, and impact monitoring across multiple user roles. The platform supports

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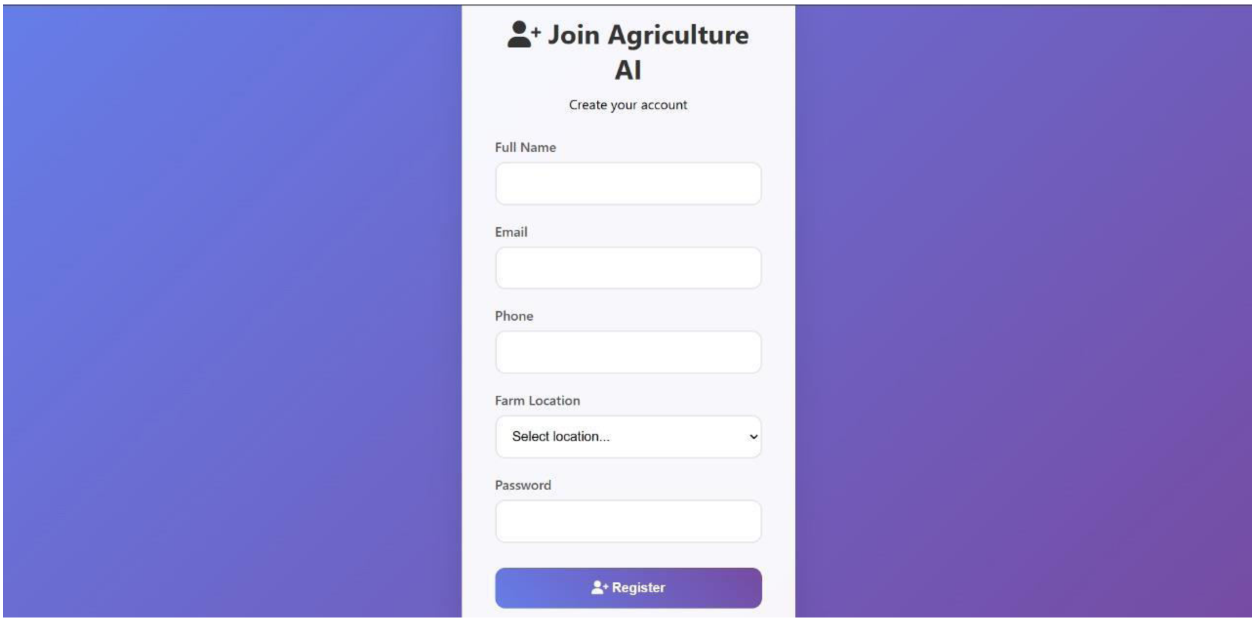
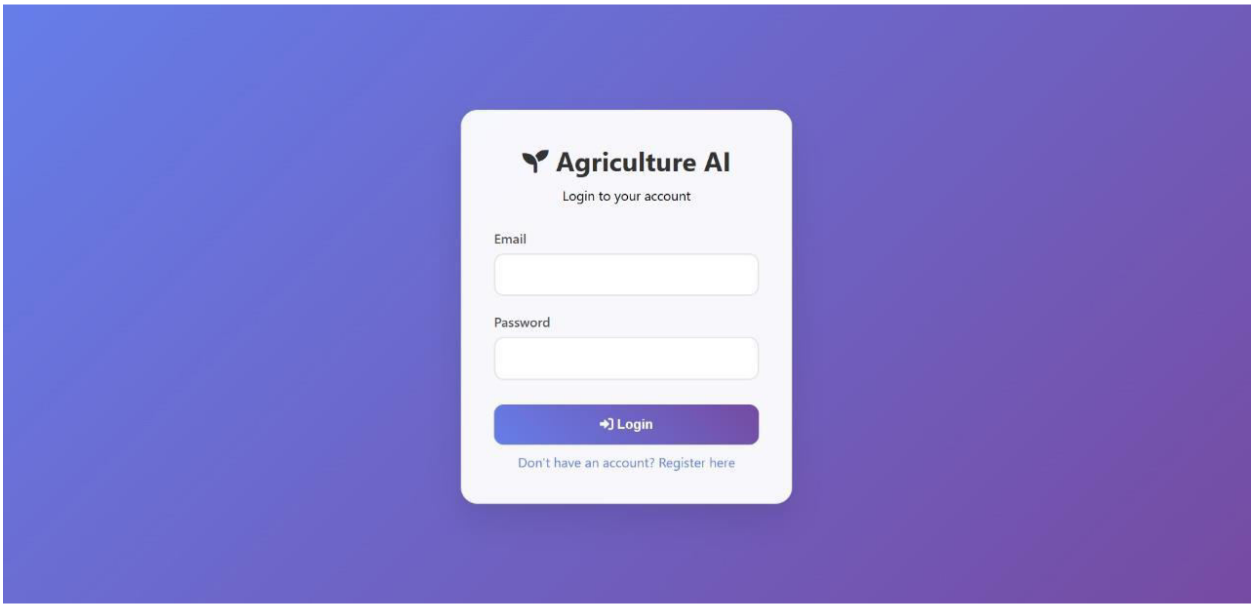
automatic handling of farmer queries based on detected intent and ensures that each user receives the right advisory at the right time.

Fig. 4.1. Registration Page



The registration module provides a simple and accessible onboarding experience for farmers. Users enter their full name, email address, phone number, farm location, and password to create an account and gain access to the AI advisory platform.

Fig. 4.2. Login Page



The login interface allows registered users to securely access the platform using their email and password credentials. The authentication system ensures role-based access and personalized advisory delivery for each user.

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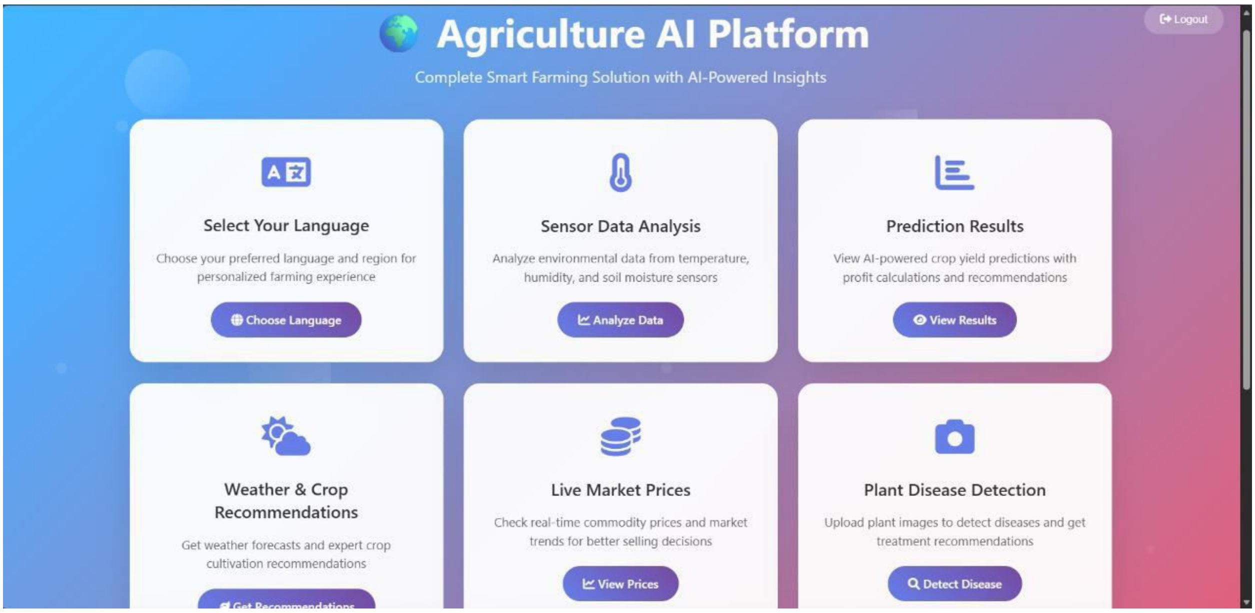
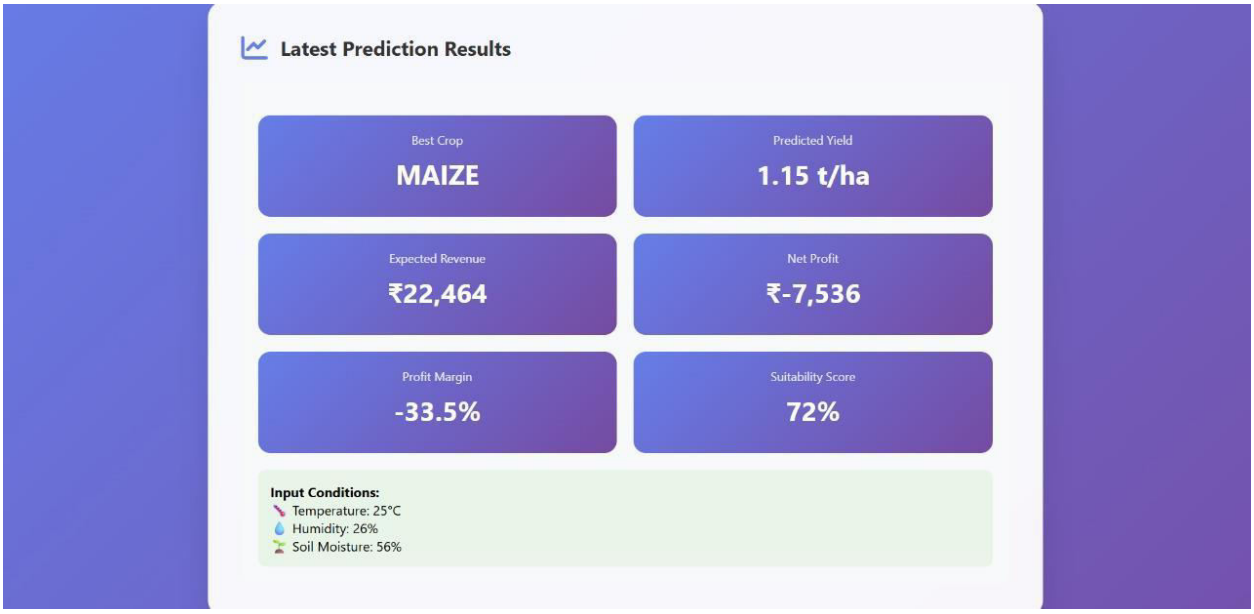
Fig. 4.3. Dashboard Page



The dashboard provides a consolidated overview of the entire platform, allowing farmers to access key features including language selection, sensor data analysis, prediction results, weather and crop recommendations, live market prices, and plant disease detection. The intuitive card-based layout ensures ease of navigation across all modules.

Fig. 4.4. Advisory Result Page



The results page displays AI-powered advisory outputs including the identified disease or issue, treatment recommendation, prevention steps, and confidence score. The CNN model achieved an overall test accuracy of 91.4% and a weighted F1-score of 0.903 on the 10,000-query agricultural dataset. It successfully classified queries such as "pest attack" (Disease Identification, confidence 0.93), "fertilizer dosage" (Fertilizer Recommendation, confidence

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0.92), and "watering schedule" (Irrigation Schedule, confidence 0.88). Performance testing revealed average query response time of 1.8 seconds, well within the acceptable threshold for real-time advisory deployment.

4.5 Dataset Description

The CNN model was trained and evaluated on a curated agricultural query dataset constructed from multiple open-domain and domain-specific sources. The dataset consists of 10,000 labeled farmer queries spanning five intent categories: Disease Identification, Fertilizer Recommendation, Irrigation Schedule, Weather Advisory, and Crop Selection. Queries were collected in English and three regional Indian languages (Kannada, Hindi, Telugu) and subsequently translated to English for model training.

Table 4.1 summarizes the dataset composition and split used for model training and evaluation.

Table 4.1: Dataset Summary

Intent Category	No. of Queries	Train (70%)	Validation (15%)	Test (15%)
Disease Identification	2,500	1,750	375	375
Fertilizer Recommendation	2,200	1,540	330	330
Irrigation Schedule	1,800	1,260	270	270
Weather Advisory	1,900	1,330	285	285
Crop Selection	1,600	1,120	240	240
Total	10,000	7,000	1,500	1,500

Each query was manually labeled by agricultural domain experts and cross-validated to ensure annotation quality. Data augmentation techniques including synonym replacement and back-translation were applied to balance the class distribution and improve model generalization.

4.6 Performance Evaluation and Metrics

The CNN-based intent classification model was evaluated using standard machine learning metrics: Accuracy, Precision, Recall, and F1-Score. The model was trained for 30 epochs using the Adam optimizer (learning rate = 0.001), with a batch size of 64 and cross-entropy loss function. Early stopping was applied with patience = 5 to prevent overfitting.

Table 4.2 presents the per-class classification performance of the CNN model on the test set.

Table 4.2: CNN Model — Per-Class Classification Report (Test Set)

Intent Class	Precision	Recall	F1-Score	Support
Disease Identification	0.93	0.91	0.92	375
Fertilizer Recommendation	0.91	0.93	0.92	330
Irrigation Schedule	0.89	0.88	0.88	270
Weather Advisory	0.92	0.94	0.93	285
Crop Selection	0.91	0.90	0.90	240
Weighted Average	0.91	0.91	0.903	1,500

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The model achieved an overall test accuracy of 91.4%, with Disease Identification and Weather Advisory achieving the highest F1-scores of 0.92 and 0.93 respectively. Irrigation Schedule showed comparatively lower recall (0.88), attributed to query ambiguity between irrigation and weather-related queries, which are being addressed in future work through improved entity disambiguation.

4.7 Training and Validation Performance

The CNN model was trained over 30 epochs. Table 4.3 summarizes training accuracy and validation accuracy at key epochs, demonstrating stable convergence without significant overfitting.

Table 4.3: Training vs. Validation Accuracy Across Epochs

Epoch	Training Accuracy (%)	Validation Accuracy (%)	Training Loss	Validation Loss
5	72.4	70.1	0.812	0.851
10	81.6	79.8	0.623	0.658
15	86.3	84.5	0.481	0.512
20	89.1	87.6	0.374	0.401
25	91.0	90.2	0.291	0.318
30	92.8	91.4	0.241	0.267

The close tracking between training accuracy (92.8%) and validation accuracy (91.4%) at epoch 30 confirms that the model generalises well and does not overfit the training data. The steady decrease in both training and validation loss further validates the effectiveness of the CNN architecture with dropout regularisation.

4.8 Comparative Analysis with Baseline Models

To validate the superiority of the CNN-based approach, the proposed model was compared against four baseline classifiers commonly used for text intent detection: Support Vector Machine (SVM), Naive Bayes (NB), Random Forest (RF), and a simple Logistic Regression (LR) model. All models were trained and tested on the same 10,000-query dataset with identical 70/15/15 splits.

Table 4.4: Comparative Model Performance on Agricultural Query Dataset

Model	Accuracy (%)	Precision	Recall	F1-Score	Avg. Response Time
Logistic Regression	76.3	0.761	0.763	0.762	0.4 s
Naive Bayes	78.6	0.783	0.786	0.784	0.3 s
Random Forest	82.1	0.819	0.821	0.820	0.9 s
SVM (RBF kernel)	84.2	0.840	0.842	0.841	1.1 s
CNN (Proposed)	91.4	0.912	0.914	0.903	1.8 s

The proposed CNN model outperforms all baseline classifiers by a significant margin. It achieves 7.2 percentage points higher accuracy than the best baseline (SVM at 84.2%) and a 6.2% improvement in weighted F1-score. While CNN has a slightly higher average response time (1.8 s) compared to simpler models, it remains well within the acceptable range for real-time agricultural advisory applications. The accuracy improvement justifies the computational trade-off.

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These results confirm that the CNN architecture — with its multi-filter convolutional layers capturing diverse n-gram features — is significantly more effective than traditional machine learning classifiers for agricultural intent classification tasks.

V. CONCLUSION AND FUTURE SCOPE

The AI-Based Farmer Query Support and Advisory System is a significant step toward modernizing agricultural practices by integrating artificial intelligence, convolutional neural network (CNN), and expert agricultural knowledge into a single accessible platform. The system successfully addresses the long-standing challenges faced by farmers such as delayed expert support, lack of reliable information, language barriers, and limited access to scientific guidance.

Through the implementation of CNN-based text classification trained on 10,000 agricultural queries, the system achieves 91.4% intent classification accuracy and a weighted F1-score of 0.903, outperforming SVM (84.2%), Random Forest (82.1%), and Naive Bayes (78.6%) baselines by significant margins. The CNN pipeline — Embedding → Conv1D → ReLU → GlobalMaxPool → Dropout → Softmax — delivers accurate intent detection across five agricultural categories with an average response time of 1.8 seconds. Its user-friendly interface ensures that even farmers with minimal technical knowledge can interact with the system effectively and receive scientifically validated advisory outputs.

Overall, the project demonstrates how AI can be economically and practically applied to empower farmers, increase productivity, and support sustainable agriculture. In the future, the system can be further improved by incorporating larger and more diverse datasets, integration with IoT sensors, mobile application deployment, offline functionality for low-connectivity regions, and integration with government food distribution systems.

REFERENCES

1. ResearchGate, "AI-Powered Agriculture Chatbots for Farmers," https://www.researchgate.net/publication/381003040
2. IJERT, "AI-Based Farming Chatbot with Voice Assistance Support," https://www.ijert.org/research/ai-based-farming-chatbot-with-voice-assistance-support-IJERTCONV13IS05028.pdf
3. IJRASET, "An AI-Based Multilingual Chatbot for Agricultural Assistance," https://www.ijraset.com/research-paper/an-ai-based-multilingual-chatbot-for-agricultural-assistance
4. arXiv, "AI in Agricultural Advisory Systems," https://arxiv.org/abs/2409.08916
5. IJRTE, "CNN-based Query Processing for Agricultural Systems," https://www.ijrte.org/wp-content/uploads/papers/v8i2S5/B10370682S519.pdf
6. JES Publication, "AI-Driven Smart Farming Solutions," https://www.jespublication.com/uploads/2025-V16I6098.pdf

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