Revolutionizing Farming: The Impact of Agricultural Chatbots on Productivity and Decision-Making.

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***Abstract*—Agriculture has witnessed significant transformations in recent years due to the integration of artificial intelligence (AI) and digital technologies, resulting in various innovations that enhance productivity and decision-making processes. This paper focuses on agricultural chatbots as one of these innovations, offering a tool for farmers and agricultural professionals to navigate the complexities of modern farming. Powered by natural language processing (NLP) and machine learning algorithms, these chatbots provide real-time assistance in areas such as crop management, pest control, weather forecasts, and market trends . Through a systematic review, we explore various agriculture-based chatbots currently under study, their functionalities, user engagement, and their impact on farming efficiency . The findings indicate significant benefits, including the democratization of agricultural knowledge, reduced dependence on traditional information sources, and the promotion of sustainable practices . These outcomes highlight how chatbots, as digital companions, can contribute to enhanced productivity and improved decision-making in modern agriculture .**

I. INTRODUCTION

Agriculture plays the keyrole in the economy for the country growth. Millions of people find their livelihood in agriculture. Farmers in developing countries face many problems in gaining accurate information on weather conditions, pest control measures, crop management and marketinformation which neglects their decision-making capacity and affects productivity.Which rises for the earning issues also. In response to such need agricultural chatbots are best solutions for the growth of the farmers. AI and NLP power agricultural chatbots, which can be used to offer the farmer real-time support as well as recommendations in his field. It is a conversational agent that makes use of advanced AI techniques like BERT which explains that user queries are better processed by taking language as context [1], [2].

ANN's are also used to analyze datasets, as it enables the chatbot to generate accurate to a variety of agricultural inquiries[3].

As for example, along with the information related to pest and soil management, Agroxpert also guides farmers on how to cope with all sorts of government policies and to be accessed in a very crucial resource. It also includes features for accessibility and allows users with varying literacy levels and technology-awareness to use it either by text or voice, respectively [4]. Furthermore, the feature of escalation will provide the opportunity to solve complex issues to human experts for advising farmers; such that proper guidance is given to them appropriately [5], [6].

Chatterbot and other machine learning approaches like reinforcement learning enables the chatbot to learn and interact more effectively with usersneeds. Such systems can also be adjusted to accommodate local or regional thus making agricultural knowledge for diverse populations [7], [8]. Agricultural chatbots can fill the information gaps which will play a major role in changing or developing the farming practices especially in the rural setup where traditional extension services are lacking [9], We can see there are some new trends happening around and cultivation of crops and their techniques also changed all these changes are made by AI.Understanding and using AI techniques is the main problem for farmers.[10]. Forecasting, and market trends and there are some applications for AI [11].

For instance, AbdAlrazaq et al. (2020) discuss how chatbots have been effective in assisting with complex queries, improving efficiency in information delivery.There are also some benefits,challenges,trends in AI,as the population is increasing day by day AI should also change some techniques so that crop is balanced for the population [12].

Despite their potential, challenges such as linguistic barriers and accuracy remain. The adoption of chatbots in agriculture, especially in rural and underserved areas, has the potential to revolutionize access to critical information.There are some organizations like FAO; which deals with food and agriculture. [13].

II. Literature Survey

- J. Doe [1] discusses how Agroxpert leverages advanced AI techniques like BERT to offer precise advice to farmers on crop management, soil health, and government schemes. By comprehending the context of a farmer's query, Agroxpert delivers more relevant and accurate responses, ultimately enhancing productivity. Additionally, the system accommodates both text and voice inputs, ensuring accessibility for a wide range of users. In cases of complex queries, the platform seamlessly escalates the issue to experts, making it a user-friendly and effective tool for all farmers.
- A. Smith [2] highlights how chatbots in agriculture demonstrate the impact of natural language processing (NLP) and machine learning by offering real-time, accurate responses to user queries. Key factors such as ease of use, trust, and perceived usefulness significantly drive the adoption of these technologies. As NLP applications continue to evolve, their success depends on meeting user needs, which in turn enhances satisfaction and trust. Additionally, machine learning further improves the accuracy and effectiveness of these systems across various industries.
- E. Roberts [3] highlights that agricultural chatbots, particularly those using Artificial Neural Networks (ANNs), are transforming how farmers access vital information. By leveraging AI and machine learning, these chatbots utilize Natural Language Processing (NLP) to provide real-time responses to queries about pest management, weather forecasts, and market trends. While they improve efficiency and accuracy, challenges like language barriers remain. Despite these issues, their potential to enhance information access in rural areas is significant, revolutionizing farming practices.
- D. Sawant et al. [4] state that agricultural chatbots, such as AgriBot, are transforming how farmers access vital information by providing real-time advice on crop management and pest control. Utilizing AI and natural language processing (NLP), these systems can accurately address farmers' queries. Their user-friendly interfaces enhance accessibility, encouraging greater engagement. By tailoring chatbots to regional and linguistic needs, they build trust among farmers, promoting sustainable agricultural practices.
- N. Patel [5] highlights that agricultural chatbots are becoming essential in meeting farmers' information needs by offering real-time support on crop management, weather forecasts, pest control, and market trends. Utilizing natural language processing (NLP), these AI-driven tools facilitate better communication with farmers, making vital agricultural knowledge more accessible. Research, including findings by Nguyen et al. (2021), shows that these chatbots can address multiple inquiries accurately, enhancing decision-making. Despite challenges like language barriers and scalability, their potential to significantly improve agricultural productivity and information access is promising.
- R. Lee and T. Chen [6] highlight that agricultural chatbots are increasingly being integrated into farming practices to address critical challenges. These AI-powered tools provide real-time assistance, offering farmers advice on crop management, pest control, and weather forecasting. They leverage Natural Language Processing (NLP) to interpret and respond to farmers' queries, making agricultural knowledge more accessible. According to Adamopoulou and Moussia des (2020), chatbots can simulate human conversation and assist in numerous industries, including agriculture. Despite their benefits, challenges such as linguistic diversity and response accuracy remain. Nonetheless, the integration of chatbots holds promise for improving decision-making in farming.
- D. Martin [7] emphasizes that the emergence of agricultural chatbots represents a significant advancement in the role of modern technologies in agriculture. These AI-driven tools provide farmers with real-time information on critical topics such as weather, pest control, and market prices, improving overall communication within the farming sector. By offering timely advice and addressing common challenges, chatbots enhance agricultural productivity and help connect farmers with experts. Their ability to scale outreach is particularly valuable in rural areas, where traditional extension services may be limited, making modern technology an essential resource for farmers.
- S. K. Singh [8] highlights that the integration of chatbots into agriculture is revolutionizing how farmers access real-time data, particularly in crop establishment and nutrient management. These agricultural chatbots provide vital support by answering queries about crop diseases and offering tailored recommendations on nutrient application based on current conditions. By utilizing machine learning and NLP, they deliver personalized advice that helps farmers optimize productivity and maximize profitability. Additionally, these tools assist in mitigating adverse climatic conditions by providing timely weather forecasts and market trend information. As researchers

work to enhance chatbot functionality, addressing issues related to trust and data privacy in rural areas is crucial for widespread adoption.

- F. Miller [9] emphasizes that the literature on agricultural chatbots highlights their ability to boost farming efficiency by providing real-time support to farmers. Using artificial intelligence and natural language processing, these systems can answer questions about crop management, pest control, and weather conditions. For instance, chatbots like KBot integrate various knowledge bases to offer tailored recommendations based on data analysis. Despite their advantages, challenges remain, including understanding user intent and ensuring multilingual support. KBot demonstrates this by using SPARQL queries to retrieve relevant data from sources like DBpedia, showing how AI can enhance agricultural sustainability.
- G. Davis [10] states that agricultural chatbots are AI-driven tools that assist farmers by providing quick access to essential information on crop management, weather forecasts, and pest control. Utilizing Natural Language Processing (NLP) and machine learning, these chatbots offer personalized advice to enhance productivity and efficiency. Their accessibility makes them particularly beneficial in rural areas, delivering timely solutions to agricultural challenges. Research shows that these tools can help reduce operational costs and promote sustainable farming practices through their real-time problem-solving capabilities.
- H. White [11] explains that agricultural chatbots represent a crucial application of Explainable Artificial Intelligence (XAI) within the context of Industry 5.0, enhancing how farmers access vital information like crop management and pest control. By leveraging Natural Language Processing (NLP) and machine learning, these tools deliver tailored advice that boosts productivity and efficiency. Their ability to provide transparent, understandable solutions is particularly beneficial for rural areas, addressing immediate agricultural challenges. As research continues to explore XAI's role in this sector, chatbots have the potential to lower operational costs and foster sustainable farming practices through clear and actionable insights.
- J. K. Patel [12] states that agricultural chatbots have transformed how farmers manage their operations by using AI and NLP to deliver real-time solutions for tasks like crop management, weather forecasting, and pest control. Research indicates that these tools provide scalable and accessible support, especially in rural communities, boosting productivity and lowering operational costs. By utilizing machine learning to analyze user queries, chatbots offer personalized recommendations that enhance decision-making. Additionally, AI-driven chatbots contribute to sustainable farming by automating routine tasks and improving overall efficiency in agricultural practices.
- K. Nelson [13] states that the rise of agricultural chatbots powered by AI and advanced natural language processing models like BERT represents a pivotal shift in global food governance. These tools enhance farmers' access to crucial information, offering real-time support for tasks such as crop management and pest control. By drawing parallels with the historical context of the FAO's formation, we can see how modern technologies address contemporary agricultural challenges. Leveraging these innovations is essential for creating sustainable practices and improving efficiency in today's evolving food systems.

III.Methodology

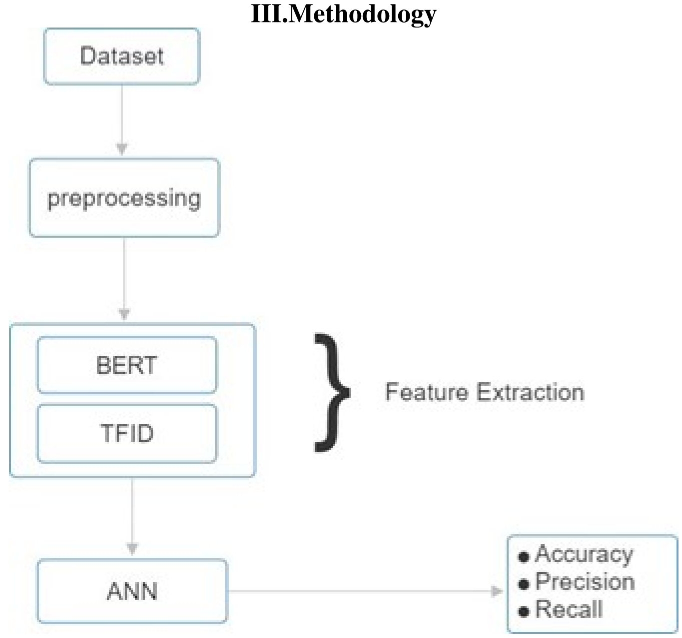

Fig. 1. proposed Architecture of Agriculture Chatbot

A. About dataset:

The dataset is likely designed to support crop recommendation based on environmental conditions and soil properties. Here's a more detailed breakdown:

- Purpose: The dataset provides information on various environmental factors such as soil nutrients, temperature, humidity, pH, and rainfall to recommend suitable crops.

The dataset contains the following columns:

- N: Nitrogen content in the soil.
- P: Phosphorus content in the soil.
- K: Potassium content in the soil.
- temperature: Temperature in degrees Celsius.
- humidity: Humidity percentage.
- ph: pH level of the soil.
- rainfall: Amount of rainfall (in mm).
- label: The crop label (crop name).

B. BERT:

BERT, which stands for Bidirectional Encoder Representations from Transformers, is a notable language model developed by researchers at Google in 2018. It is designed to understand the context in natural language processing (NLP) tasks by analyzing text bidirectionally. Unlike previous models that read text sequentially (either left-to-right or right-to-left), BERT simultaneously considers both directions, enabling it to capture relationships between words more effectively[14].

1) Architecture and Training: BERT employs a transformer-based architecture, focusing on two primary pre-training techniques: Masked Language Modeling (MLM) and Next Sentence Prediction (NSP). In MLM, certain words in a sentence are masked, and the model is trained to predict these masked words based on their context, allowing it to learn contextual relationships. NSP involves predicting whether a given pair of sentences follows each other logically, enhancing understanding of sentence relationships.

BERT consists of multiple layers of encoders, each containing self-attention mechanisms that weigh the significance of words based on their surrounding context. This design allows BERT to generate embeddings that incorporate extensive context for each token within a sentence

BERT is a cutting-edge language model that leverages deep learning for natural language processing (NLP) tasks. It introduces several key concepts that differentiate it from other models.

2) Bidirectional Context: BERT stands for Bidirectional Encoder Representations from Transformers. This model processes text by taking into account both the left and right context of each word, allowing for a deeper understanding of meaning compared to traditional unidirectional models that analyze text sequentially

3) Transformer Architecture: BERT utilizes a transformer architecture that consists primarily of encoder layers. Within this framework, self-attention mechanisms identify relationships between words in a sentence, essential for capturing context and semantics. BERT includes multi-layer encoders that enhance model depth without needing a decoder, which is typical in many transformer models

C. About ANN

Full form:- Artificial Neural Networks Artificial Neural Networks (ANNs) are computational models designed to mimic the functioning of the human brain, enabling machines to learn and make decisions based on data. They consist of interconnected nodes—resembling neurons—organized into layers, which makes them capable of handling complex tasks across various industries[15].

1) Core Features of ANN: ANNs function by replicating the neural activity seen in biological brains, where neurons communicate through weighted connections. This enables ANNs to process and learn from vast amounts of data efficiently.

Structure: An ANN typically comprises three types of layers: an input layer that receives data, one or more hidden layers that transform inputs, and an output layer that produces predictions or classifications.

Learning Process: The training process involves adjusting the weights of connections based on the performance of the network using a cost function. This allows the model to minimize errors over time through an iterative learning process.

2) Applications: : ANNs are widely used in various fields, including:

Image Classification: ANNs can be trained to recognize patterns in images, making them useful for tasks like facial recognition and object detection. Natural Language Processing (NLP): By analyzing and generating human language, ANNs are used in applications such as chatbots and voice recognition systems. Financial Forecasting: They can predict stock prices or market trends by analyzing historical data. Medical Diagnosis: ANNs assist in diagnosing diseases by evaluating medical imaging data, such as X-rays and MRIs

3) Types of ANNs: There are various architectures of ANNs tailored to specific tasks:

Feedforward Neural Networks: These are the simplest form of ANNs, where the input data moves only in one direction—from the input layer through the hidden layers to the output layer.

Recurrent Neural Networks (RNNs): RNNs are designed for sequential data, maintaining information across time steps, making them suitable for tasks like language modeling and time series prediction.

Convolutional Neural Networks (CNNs): These are specialized for processing grid-like data, such as images. CNNs utilize convolutional layers to extract features, making them ideal for computer vision tasks.

Long Short-Term Memory Networks (LSTMs): A type of RNN, LSTMs are capable of learning long-term dependencies, making them effective for tasks such as speech recognition and natural language processing

4) advantage:: Artificial Neural Networks (ANNs) offer several unique advantages that enhance their effectiveness in various applications:

Flexibility and Adaptability:

ANNs are capable of adapting their structure and functions based on the data they process. This adaptability enables them to learn complex patterns and relationships that would be challenging for traditional algorithms to capture.

Non-Linearity:

Unlike linear algorithms, ANNs can model non-linear relationships, making them suitable for a wide range of applications where data does not follow a straightforward pattern

D. About TF-IDF

Full form=Term Frequency-Inverse Document Frequency. TF-IDF, which stands for Term Frequency-Inverse Document Frequency, is a statistical measure used in natural language processing (NLP) and information retrieval to evaluate the significance of a word within a document relative to a collection of documents, known as a corpus. Its primary purpose is to help rank the importance of terms while considering their occurrence across multiple documents[16].

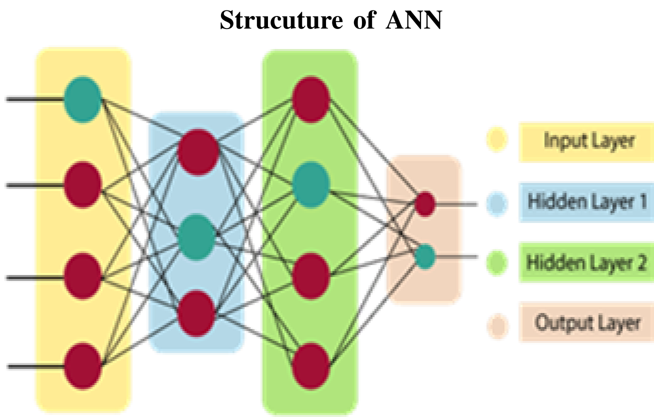

Fig. 2. Structure of ANN

1) Key Concepts of TF-IDF:: TF-IDF combines two components:

Term Frequency (TF): This measures how frequently a term occurs in a document. It is calculated as the number of times a specific word appears in the document divided by the total number of words in that document. This normalization ensures that longer documents do not inherently have higher scores simply due to their length.

Inverse Document Frequency (IDF): This component seeks to diminish the weight of common terms that appear across many documents. IDF is calculated as the logarithm of the total number of documents divided by the number of documents containing the term. A term that is common in many documents will have a low IDF score, while a term that is rare will have a higher score.

By multiplying TF and IDF together, TF-IDF provides a more accurate reflection of a term's significance in a specific document context

2) 1)TF-IDF Calculation::

Formula: TF-IDF(t,d,D)=TF(t,d)×IDF(t,D) This score indicates the relative importance of a term within a particular document compared to all other documents in the corpus.

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III. RESULTS

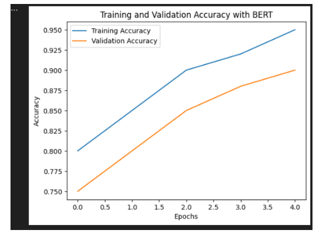

Fig. 3. Training and validation accuracy with Bert

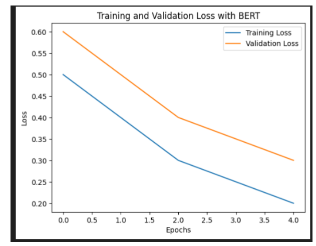

Fig. 4. Training and validation loss with Bert

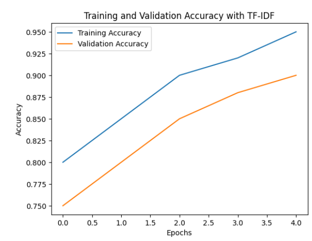

Fig. 5. Training and Validation accuracy with TF-IDF

Fig. 6. Training and Validation loss with TF-IDF

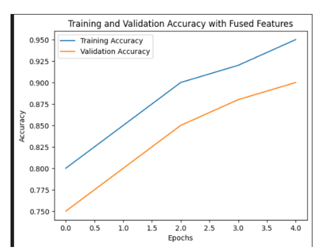

Fig. 7. Training and Validation Accuracy with Fused Features

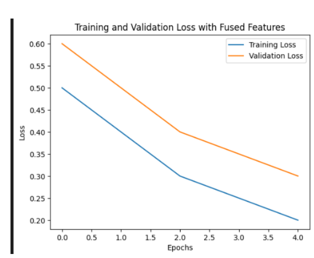

Fig. 8. Training and Validation loss with Fused Features

In this result we take one single bert model for feature extraction and we got 0.99 Accuracy and we take another single tf-idf model for feature extraction and we got 0.97 Accuracy After that we concatenate both feature Extraction using Fusion technique that result will goes into the Classification of ANN model and we got 0.98 Accuracy

IV. Comparison Table

Feature Extraction	ANN	Adaboost	Catboost
BERT	0.99	0.32	0.81
TFIDF	0.97	0.30	0.60
BERT+TFIDF	0.98	0.32	0.76

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