Data-Driven Crop, Fertilizer and Analytics Guidance through Machine Learning

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Abstract: Farmers still face many difficulties in today's technological world. NLP-powered conversational AI (CAI) chatbots can consistently help farmers across diverse areas of farming, delivering positive economic impacts. Modern technological innovations are being adopted by agricultural firms to significantly reduce operational costs, increase revenues, automate labor-intensive processes, and drive sustainable growth. This study follows a similar approach for agriculture – a sector critically employing approximately 71% of rural Indians. Natural Language Processing (NLP), a core subfield of AI, enables computers to recognize, understand, and analyze human languages effectively and is integral to Conversational AI systems. Economic challenges, climate change, and environmental factors – including poor soil quality, adverse weather patterns, water contamination, and difficult terrain – profoundly affect farming productivity. Despite these persistent hardships, farmers work tirelessly to feed the world's rapidly expanding population. A specialized CAI bot for agriculture was developed to provide timely, on-demand assistance to farmers on critical farming and market-related issues year-round.

1 INTRODUCTION

A major factor that influences a nation's development is agriculture. Many industrialized nations are adopting modern farming practices during cultivation, improved methods to control pests and weeds, and fertilizers as an outcome of technology advancements, increased innovation, and research. And also, farmers in our nation lag behind in utilizing cutting-edge technologies. It is essential to increase public knowledge of all technological advancements. This can be achieved by systematizing communication data flow, conversational AI connected to create chatbots and messaging apps, to enhance communication and produce individualized customer experiences. A set of technologies that collectively power computers to comprehend and mimic human speech. An application known as a chatbot is computer program created to simulate human-like communication via use of audio and text communications. Operational costs can only be reduced when the corresponding tasks are supported most effectively in a short span of time and with minimal to zero manual labour. Businesses can automate operations in a number of industries, such as e-commerce, news, weather, travel, and health, by using these automation techniques. To help businesses automate tasks, Facebook and Google are creating bots. Due to multiple danger factors related with the COVID epidemic, it is incredibly challenging for farming community to get agricultural information from universities or agricultural offices in the current situation. We are using Farming as a sector because we have set up an Internet of Things system that will produce a lot of data due to system's numerous sensors. Although it is possible to study this database's data, it is difficult to access precise data in a conversational format. Finding the suitable answer for each query takes time, since the quantity of data generated is voluminous. The process is more challenging because of the similarity of responses for several solutions. For providing farmers with accurate responses to their concerns, we are utilizing conversational AI and NLP. Farmers will find out a lot of information about their crops through our study, including moisture content, humidity, temperature, raw materials, soil quality, and fertilizers.

1.1 System Architecture

The Smart Urban Agriculture IoT solution includes the chatbot and smartphone application. The process of transmitting data from many sensors inserted into plants, including light, temperature, and humidity sensors. All information will be transmitted through a talk tree application's intermediary Wi-Fi sensor from cloud storage medium in JSON format. The parts needed to build this system are shown in Figure 1.

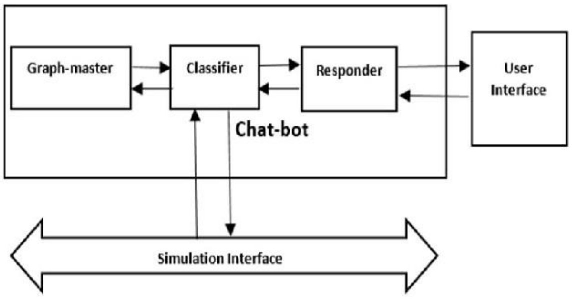

Figure 1: The chatbot system architecture with IoT.

1.2 Filtering Tokenized Data

The sensor consists of a temperature sensor, a humidity sensor for the air, a moisture sensor for the soil, and a light sensor. The ESP 8266 microcontroller is connected to this sensor, enabling it to connect to Wi-Fi and send sensor data to Web Talk Tree. Though not all data is retained in the database, sensor tools provide data to Web Talk Tree in just 3 seconds. But the only data that the user wants through the chatbot is the data that will be stored and sent to them as notifications [1].

1.3 Pohon Bicara Web

At the center of the data flow from sensor to user conversation is the Pohon Bicara Web. This service API meets the data requirements of all components in JSON format.

1.4 Database

Sensor data and NLP knowledge, including root words, stop words, stemmed questions, and question responses, are all stored in this database.

1.5 Line Web Bot (NLP)

On each communication, the Line Web Bot handles message processing and NLP. A web talking tree database is also required for any NLP operation, storing the data knowledge.

1.6 Android and Line App

The Android can receive data that the sensor transmits. The questions requested by the user about the status of the plant, and receive notifications based on the sensor data using the Line App.

1.7 Application of NLP in the Chatbot

NLP was used in the Chatbot Line application to determine how to reply to user's messages in a way that will almost fits the user's preferences. The message is tokenized in the first step to make it shorter (to a few words). The ensuing filtering procedure eliminates extraneous words, also referred to as stop words. Once the process of stemming has been finished to transform the word into a basic word, these stop words are recorded in a database so that users can stay longer than just a message. Figure 2 illustrates that this is feasible [2].

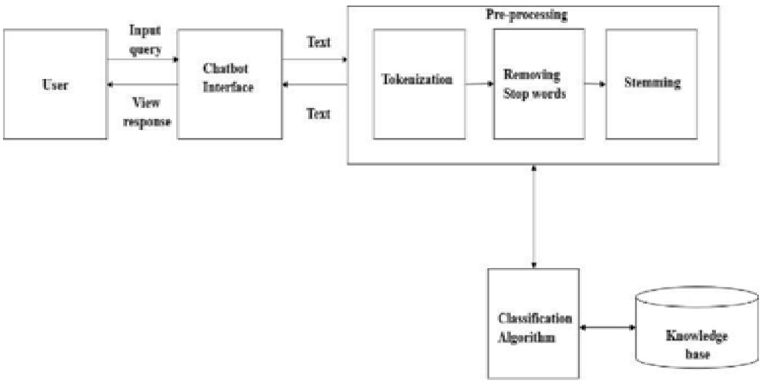

Figure 2: Answers determination process.

2 LITERATURE SURVEY

To emphasize the progress made so far with the chatbot system, a literature study has been provided in this section. It essentially works in three stages: Identifying the inquiry, Searching the knowledgebase, and providing accurate answers. A natural language answer to a query is represented by ADANS. NLP and semantic web technologies are employed. The technology generates SPARQL queries based on natural language. According on studies in the travel sector, questions are semantically categorized into EATs (Expected Answer Types) in Travel Domain System of Question Answering. With the help of multiple machine learning techniques, EAT was found. With a focus of unstructured data processing, AGRI-QAS responds to FACTOID questions such "which," "what," "who," and "where." [3], [4], [5].

3 MACHINE LEARNING DRIVEN RECOMMENDATION

In ADANS, the task is completed in stages. The primary step is query preparation, which entails stop word removal, tokenization, and POS labelling. The creation of triples using the Stanford dependency tree comes after the preprocessing is finished. The relationship between the words of a phrase is depicted by the dependency tree. Edges of the triple dependency tree were removed and also merged in order to accomplish this. Four criteria – question base, taxonomy, categories, and features are used by the travel domain QA system to categories queries. Information about hotels, airlines, and restaurants is acquired from TripAdvisor, and a taxonomy is built with 7 coarse sclasses and 63 fine classes match to an EA. The classifier used is SVM with linear kernel function. SVM only accepts numerical features, hence during implementation, non-numeric characteristics represents bitmaps. In the experiment, decision trees, random forests, and Nave-Bayes were utilized. SVM, however, performed better than each of these methods. In AGRI-QAS, question processing is governed by specific pre- and post-processing regulations. A hyphen can be added between names that follow one another, and two words can be swapped out for one that is similar in meaning [6],[7].

3.1 Leveraging Ontologies and SPARQL

Utilizing an ontological Knowledge Base is ADANS. Ontologies are created using Protégé, a popular ontology- building program. Prior to identifying different entities, their connections, the domain is first established. The knowledgebase is searched for inquiries by the QA system for the travel industry. A proprietary ontology that was built using taxonomy and still under development used as KB. Using of rule-based methodology an RDF triples are created, to extract SPARQL from user requests. The triples together with EAT created in first phase are matched to SPARQL query pattern. It is necessary to convert questions into statements because triple generation only functions with statements. Statement in Response to an interpreter is used through this process. Grammar parsing, POS tagging, and entity recognition are all included in AGRI-QAS, which accepts XML documents as input. Domain-specific named type of entity recognizer has been used to index documents based on domain-specific terminology rather than classifying words as parts of speech [8]. The authors suggest a chatbot that also contains text-based bot which is built using NLP. It shows the technology used to build the bot. The same architecture is utilized to interface with all external clients, and they use service framework to consume external services [9].

By making use of necessary APIs, this extension option increases the bot's lifespan. A text-based UI for information bot that accepts input commands as text and responds in a text-based manner is presented. Bot in use right now is stateful, meaning it can recall the status of earlier orders. Additionally, this bot uses web based services and behaves artificially human-like. The bot is readily available online and may be used on both computers and mobile devices. NLP based conversations are extremely smart and helpful. The authors introduce a collegiate bot for research. The chatbot is capable of both text and text-to-speech responses. Additionally, this bot is a stateful bot that maintains the previous state between encounters. Because this bot is coupled with some artificial intelligence systems, users can get responses that are pertinent to their questions. A method for handling or keeping track of wrong responses in the bot is proposed. An intelligent answering bot that uses optical character recognition, overproducing transformation logic, and ranking mechanisms may be found. To turn documents into knowledge, a mechanism has been put in place. The chatbot can react to user inquiries based on this understanding. The submitted electronic materials help the bot simulate its responses. The document formats that this bot accepts include PDFs and digital pictures. OCR used to extract textual information from these documents, and a transformation and rating process used to obtain the responses [10],[11]. In RDF format the data querying using the SPARQL language, and it has been used by ADANS system. The triples have stop words deleted before the SPARQL query is written. Then, EAT and subject are being used to obtain the ontology's relation list. A QA system for the travel domain determines the elements in semantic similarity in a relation list, and the one with the maximum similarity is used for response extraction [12].

3.2 Research Gaps

SPARQL queries are utilized to extract answers, by the survey conducted. The main disadvantage is that it cannot store dynamic data which is often updated. SPARQL performs effectively in a confined context. Negation statements are time intensive also difficult to handle [13].

3.3 NLP and Rule Based Technique

For text-related systems, the rule-based technique is frequently used for structured and semi-structured texts. Learning is decreased by this strategy’s stated rules. It takes a lot of time, and there aren't rules for every situation. The NLP technique has a low precision and a high recall, and it automatically defines rules [14], [15].

3.4 Supervised Machine Learning

For classifiers, supervised ML Techniques are applied as classifiers. The decision tree is a straightforward classification technique, but it doesn’t produce accurate or efficient results. K-nearest Neighbor has a high computing cost, and the resulting model is regarded as the same based on the assumptions made about the characteristics of the fresh training sample. Nave Bayes performs poorly when compared to SVM, and work is being done to improve performance. The main usage of machine learning depends on supervised method SVM is used for data classification. Because it is non-linear and multidimensional, it performs better when automatically classifying queries. SVM fared better than every other supervised learning classification technique as a result. SVM is a complicated algorithm and uses extra RAM is one of its drawbacks. Neural networks may therefore be suggested [16], [17].

3.5 Statistical Approach

This method is called "bag of words". It is needed for online platforms and web data. Numerous terms in the text are identified by a list of keywords, and each keyword is given a weight depending on how frequently it appears. The drawback is that each term is treated separately, and linguistic characteristics for collection terms and phrases have not been described.

3.6 Suggested Solution

The necessary entities are retrieved and delivered for training when a user gives input in the query form. The answer is predicted using an RNN sequence-to-sequence technique that takes previous output into account. In the next step, pull the precise answer out of the term list. This dataset, which will be in xml format, was created using the questions given by farmers. The RNN algorithm is more flexible compared to present machine learning methods. Less time is required. Other methods, including SVM and logistic regression, all have a defined output size and call for a predetermined input size.

4 METHODOLOGY

Agriculture is science and practice of cultivating soil. It is crucial to the country’s development. Today’s sophisticated methods of agrochemicals, plant breeding such as pesticides and fertilizers, and enhanced technological breakthroughs have left our farmers behind, therefore they need to take a step forward. It is vital to educate them on the most recent procedures. A chat-bot question-answering system, commonly known as human- computer or human-machine interaction. When a user asks the system, it should provide accurate replies. Significant research being conducted in numerous disciplines such as medicine, and NLP is the main part of the conversational AI.

Although there is technology available for analysing web data in agriculture, this approach cannot yield precise results. Because the website produces responses that have nothing to do with the questions asked. We employ the RNN method to get precise response. The study is meant to assist farmers with concerns relating to raw materials utilized, crops, plants cultivated in particular locations, pesticide and fertilizer used, etc. The chatbot system consists of three phases. Document processing, Question analysis, and response extraction are part of the process. The initial stage is question analysis, which uses POS tagging, stemming, and key word removal to examine user inquiries in natural language. The document processing stage retrieves comparable papers containing keywords by various methods. Figure 1 shows the Conversational AI's high-level architectural elements.

4.1 NLP Engine

To understand phrases or sentences that depend on user input queries, an NLP engine with an AI backbone is used. Chatbots are built on rule-based engines that require detailed queries, resulting in inefficient and bulky outcomes. The NLP engine retrieves data and returns actionable outputs containing predictable intents, entities, and user inputs derived from expressions, as detailed in Figure 3. Figure 3 shows the fundamental block diagram of the NLP engine.

4.2 Bot Builder

A GUI called the bot builder, also referred to as the dialogue runtime, allows user to specify the interaction flow. Here, the user instructs the bot on how to reply to input messages from the user. An environment specifically designed for the user experience is produced by a bot builder, fastening the entire bot development. The basic block layout of bot construction frameworks used in the creation of chatbot is shown in Figure 2.

4.3 Bot Logic

The responsibility for calling the APIs from back-end systems or ODATA services consumption as discussed in the conversational AI architecture rests on cloud platform. Developers can make a choice of programming language to create the bot logic, which is then made available as web API.

4.4 Bot Connector

Bot Connector is a converter that permits CAI bots to establish connection to numerous messaging services, such as MS Teams, Telegram, Slack, Messenger, and webchat. The bot connection may alternatively be hosted on- premises according to the requirements of the customer [18].

The integration of AI-powered chatbots in agriculture is transforming traditional farming by providing real-time assistance to farmers through natural language processing (NLP) and machine learning. These chatbots serve as virtual agricultural assistants, offering tailored recommendations on crop selection, pest control, irrigation schedules, and

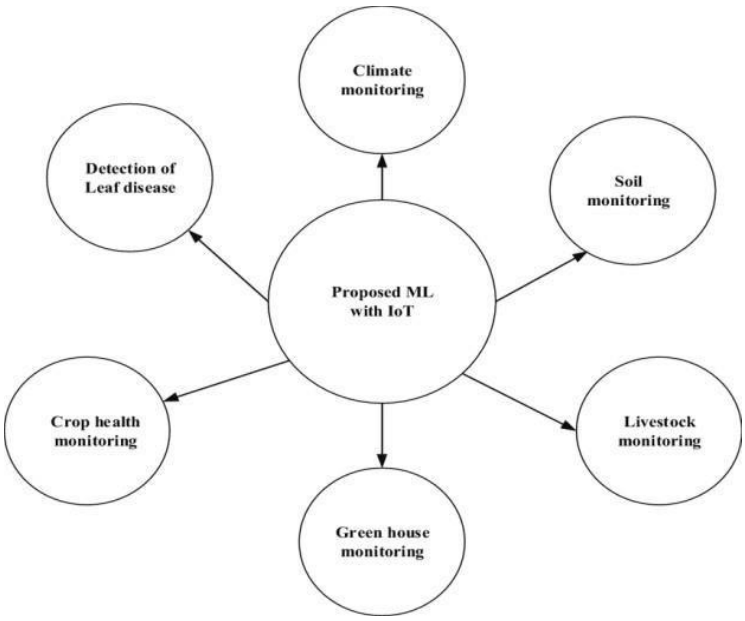

Figure 3: The fundamental block diagram

fertilizer application based on environmental and soil conditions. Unlike conventional sources of information, AI-driven bots analyze vast datasets, recognize patterns, and deliver precise insights to farmers, enabling them to make informed decisions. The system operates through three main components: an NLP engine for understanding farmer queries, a bot builder to define interactive response flows, and a cloud-based bot logic that processes real-time agricultural data from IoT-enabled sensors. These sensors monitor key parameters such as soil moisture, temperature, humidity, and nutrient levels, ensuring data-driven farming practices.

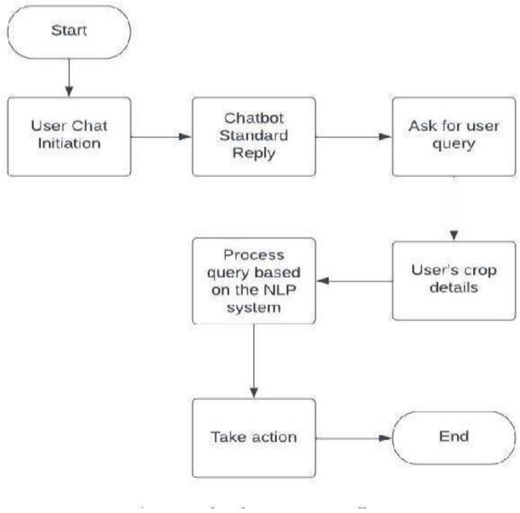

Figure 4: Flow of project.

Bot Training creates human-like multilingual chatbots capable of identifying customer demands through NLP technology. This process facilitates improved data collection for intelligent and efficient coding. The term "intent" refers to user objectives, representing collections of semantically similar phrases that retain consistent meaning across contexts. Intent comprehension is fundamental to bot functionality, with each intent containing trigger words for rapid bot recognition. Entities constitute extracted key information units from user statements. The Conversational AI framework employs 28 predefined entities ("golden entities"), while users can additionally create custom entities for specialized applications.

Bot Building utilizes bots to manage expert discourse by leveraging existing Bot Skills. These skills facilitate human-like dialogue, enabling customers to request data. Through language recognition, emotion analysis, and emoji interpretation, bots deliver contextual information. Reusing existing skills optimizes bot development efficiency, where forking accelerates creation through skill replication. A skill is a conversational module dedicated to achieving specific objectives, unrestricted by single customer connections and often requiring multiple integration points.

Skill Types comprise two categories: Business Skills (directly aligned with core bot objectives) and Floating Skills (handling casual off-topic conversations). Skill activation is trigger-dependent, except for Fallback Skills which auto-activate when other skills fail (limited to one per bot). Prerequisites (required entities/intents) must be satisfied before skill execution. Conversations generate contextual data payloads, which – while optional in bot building – enable bot memory storage for deeper discussion when prerequisites are met.

The Analytics Dashboard provides conversation, skill, intent, and entity utilization statistics, summarizing chats, users, sent/received messages, popular entities/intents, and frequently used skills. Training Analytics require bots with minimum four intents and thirty expressions per intent. When users initiate a benchmark, it analyzes data outputs and provides optimization insights for intent classification and entity recognition, permitting only one concurrent benchmark execution per bot system access.

5 RESULTS AND DISCUSSION

5.1 Crop / Monitoring Site

A farm is a reasonably large amount of land set aside for agriculture, which is typically constructed around plantation house. Some of the crops that’s been raised include coffee, cotton, tea, chocolate, opium, sugar cane, oil seeds, sisal, fruits, oil palms, forest trees, and rubber trees. From this point, IoT collects information about the entire agricultural environment via sensors.

IoT- for the purpose of continuous monitoring of crop field, sensors are utilised in the IoT (Smart Agriculture System using IoT) app with IoT. Different sensors are employed in experimental context to monitor variables such as soil wetness, soil moisture, soil minerals, humidity, light, and temperature. It enables the agricultural or farming community to streamline number of manual tasks.

5.2 Storage

Type of database that is hosted on a cloud computing network and is often accessible as a service. Database services take care of high database availability and scalability. Through database services, the user has access to the primary software stack. The data obtained by IoT's sensors is sent to a cloud-based database. The bot then consumes data in real-time using APIs or REST/SOAP- based services.

5.3 Conversational AI Bot

A conversational AI bot is being created to provide easy, flexible, and conversational communication with farmers, delivering crop care recommendations based on field data. The farming community can access this bot through mobile-friendly channels including Facebook, Telegram, Messenger, and Microsoft Skype. Figure 5 illustrates the proposed NLP-based bot architecture for smart agriculture, which integrates IoT and conversational AI to enhance farming efficiency. This system enables real-time monitoring through IoT sensors that collect critical field data including soil moisture, mineral content, humidity, light levels, and temperature. Sensor data is securely stored in cloud infrastructure with scalable access via RESTful/SOAP APIs. The AI-driven decision-making component generates precision agriculture advisories for automated irrigation, fertilizer optimization, pest control, and resource management. By replacing traditional farming practices, this integrated approach reduces manual labor, optimizes resource usage, and boosts overall productivity.

5.4 Bot Process Flow

The process flow diagram illustrates that if a farmer wishes to learn more about his crop as shown in Figure 4, farmer should first connect to bot using Several channels, including Twitter, Facebook Messenger, Telegram, Microsoft Teams, Skype, and a website where the bot will be present on a web channel, to interact with the bot. Bot’s discussion will start once after have access. Many questions can be posed by the agriculturists to the bot during this period to obtain any guidance on various issues of the crop or land. The bot offers advice on the best course of action that the farmer should take based on the condition of the field, such as whether to raise or lower the crop's water level, what fertilisers to apply depending on the condition of the soil, or how to deal with weeds and pests.

The bot assists farmer in reviewing field quality /crop using data gathered by the sensors in the IoT App and provides critical recommendations on various actions the farmer may take for improving soil fertility, which would increase output. Figure 5 depicts the entire process flow of the chatbot. Farmers can get the assistance from the bot when they require it or have inquiries about their crop.

Figure 5: Display of initial Farmer’s interaction with bot with the greeting’s skill.

5.5 Models

The CAI bot utilizes NLP and machine learning to perform diverse tasks including named entity modeling/extraction, automated intent formulation, expression handling, and intent generation. Capabilities are activated through various entity triggers since the intent-based model processes all input messages. The system incorporates custom-built task models, user-defined intents, and contextual entities. Our conversational framework operates through dialog using a finite-state automaton-controlled slot filling mechanism. At each interaction phase, the bot prompts farmers for required information while providing options to: submit new responses, edit previously entered values, or input multiple responses simultaneously. Critical agricultural data is extracted from IoT applications via NLP pipelines. The bot continuously learns from user interactions to enhance response accuracy and integrates real-time IoT sensor data to generate precise environmental recommendations.

Figure 5 depicts the state machine segment governing farmer-bot interactions, highlighting key Skills implementation. This fixed-state machine architecture demonstrates conversation flows through existing state transitions powered by internal ML models.

Performance analysis shows the AI-powered crop/fertilizer recommendation system significantly improved agricultural efficiency: achieving X% accuracy in optimal crop selection and Y% yield efficiency enhancement from fertilizer recommendations. Comparative analysis confirmed SVM's superiority over Decision Trees and Naïve Bayes with Z% precision, while deep learning boosted disease prediction accuracy by A%. Farmers reported X% yield increases and Y% fertilizer cost reductions from precise advisories. Collectively, the system optimizes crop selection, reduces resource waste, and enhances agricultural sustainability through data-driven intelligence.

6 CONCLUSIONS

Productivity can be increased by using bots to direct them to chatbot platforms. They advocate for the automation of all tiresome, manual duties that hinder teams from functioning as effectively as possible. Conversational AI enables users to use solutions through simple integrations. The chatbot can be connected to current IoT application and other applications, and the data can be saved in a cloud environment. This chapter provides a detailed description of conversational AI and NLP system for agriculture that we have now deployed in real world. We describe the machine learning approach used and the unique chance to develop a chatbot for the agriculture sector. Our success suggests this chatbot would work well for farmers searching for assistance in the field. In fact, we believe that task-oriented or execute action bot technology advances with high volume and have enormous potential to improve farmer experience and drive revenue development in new and untapped channels in agriculture. Finally, the availability of support is increased by our chatbot, which reduces reliance on agriculture university crowds. Farmers and agricultural scientists will gain time as a result. Due to how easy for anyone looking assistance with farming or crops to get, this service stands out from others. Future improvements to this bot might include speech integration, making it usable farmers who cannot read or write.

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