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Implementing AI-Powered Chatbots in Agriculture for Optimization and Efficiency

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***Abstract*— Agriculture is critical to the global economy, therefore the introduction of automation in this field is now an essential and rising topic internationally. Demands for food and labor are rising at an exponential rate, outpacing the capabilities of conventional farming practices. A new age of revolutionary change has been caused by the incorporation of Artificial Intelligence (AI) into agriculture. This study focuses on the development of an AI-powered Chatbot that is customized for the agricultural sector, offering assistance with crop recommendation and disease detection. The two machine learning models used to handle crop suggestions are Gaussian Naive Bayes (GNB) and Support Vector Machine (SVM). Using the VGG-16 transfer learning model, disease predictions are made. The models are evaluated thoroughly, and as a result, GNB and VGG-16 are chosen to be a part of the Chatbot's architecture. Without the need for professional knowledge, the Chatbot can help farmers select crops that are suited for cultivation and evaluate the health of their crops. The designed Chatbot is confirmed to be reliable and effective after extensive testing of its performance through various queries. By utilizing AI, we made a smart tool for effective crop management and harvesting.**

Keywords*— *Chatbot, Agriculture, Gaussian naïve Bayes, Plant Disease, Crop Suggestion, VGG-16

I. Introduction

Agriculture, the oldest and most significant occupation known to humans, has evolved over time without a distinct origin point. Agriculture requires innovation and technology since the demand for agricultural products has increased due to population growth [1]. The agricultural industry has warmly welcomed AI. AI has the potential to drastically revolutionize the agriculture industry by increasing efficiency, minimizing waste, and raising crop yields. According to MarketsandMarkets, the AI market for agricultural applications will grow at a fantastic 35.6% CAGR (Compound Annual Growth Rate) between 2020 and 2025, from $2.35 billion to $10.83 billion.

AI has the ability to gather and analyze huge amounts of data in order to address the world's food security challenges, allowing farmers to make better decisions and boost crop yields. Farmers can use AI to track soil health, crop development, and weather trends, which allows them to detect diseases early and take precautionary measures [2]. AI also aids in weather forecasting, which is beneficial to farmers because it allows them to plan ahead and choose the optimum periods to plant. Furthermore, AI aids in the optimization of resource usage and the reduction of waste. Farmers can accurately regulate the amount of water and fertilizer supplied to crops using AI, resulting in more sustainable and environmentally friendly practices. By lowering the likelihood of soil and water pollution, this optimization addresses modern environmental concerns. Many farmers, particularly smallholders, lack the resources to invest in AI systems, despite the fact that these systems would significantly boost agricultural output. Smallholder farmers struggle to deploy AI systems efficiently due to financial constraints and a lack of access to technical expertise. Chatbots are popular in the field of AI because of their ability to react swiftly to frequently asked inquiries [3]. These bots imply quick responses and easy access to data for farmers. Chatbots have evolved into highly effective resources for resolving a wide range of challenges faced by farmers as a result of advances in machine learning.

There are several AI-based agricultural applications, in this work we focus on Chatbot development. The developed Chatbots aid farmers in two ways. The bot initially suggests crops to produce based on soil and weather conditions. Another advantage is that it can analyze images provided by users to diagnose crop illnesses. Methods such as VGG-16 for disease diagnosis and SVM and GNB for crop recommendations aid in this effort. Finally, these models are used for developing and launching the Chatbot that would assist farmers.

II. RELATED WORKS

The main focus of the paper [4] is to create a Chatbot capable of identifying plant diseases, classifying them, and answering queries about treatment choices and potential treatments. The major purpose is to assist farmers in increasing agricultural productivity and decreasing plant disease incidence. When it detects a disease, the Chatbot will send a link to the farmer with prevention instructions. The data set includes a wide variety of plant species, including rice, maize, tomato, and apple, each with its own set of symptoms that were evaluated using machine learning and Python. The computed sickness score, which is based on a confidence-level methodology, indicates the crop's treatability. If a plant's disease score is 15% or less, it is regarded to be recoverable; if it is more than 50%, it is thought to be dead. It is feasible to treat the crop for percentages ranging from 15% to 50%. The study [5] recommends AgroBot, a multi-user chat program, to help farmers keep up with the ever-changing market. Farmers will be able to adapt to new technology and satisfy the changing wants of their clients with the help of the Chatbot. The project's scope includes developing a Chatbot that asks farmers to send images of their crops. A Deep Learning CNN algorithm is used by the Chatbot to diagnose agricultural ailments and give potential solutions. Following that, users can ask the Chatbot questions about crops, such as what the crop is named, and the bot will respond with information about soil, rainfall, and other relevant statistics. By integrating image identification with helpful discourse, this strategy increases farmers' awareness of agricultural situations and assists them in making decisions. According to the study [6] a LINE Chatbot app might represent knowledge and information and assist farmers with guidance on how to produce their crops. This Chatbot can be used to operate drip irrigation, mist irrigation, the home page, and the start/stop menu. It is used in conjunction with smart agriculture and recommendation systems. The Chatbot provides farmers with data monitoring tools to aid decision-making, allowing them to operate irrigation systems, and answer questions about agricultural conditions. Farmers were pleased with the results of employing this LINE Chatbot app; in fact, 96% were pleased. Remember that the chatbox interactivity is based on scripts or rules.

Research [7] indicates that farmers are facing challenges in keeping up with the constantly changing market. One potential answer is AgroBot, a multi-user chat program. The Chatbot overcomes constraints by identifying and processing farmer demands using Natural Language Processing (NLP). It identifies the most essential terms and queries, compares them to a database of information, and gives the best results. Through this method, farmers can simply communicate with the Chatbot, allowing them to keep up with agricultural techniques, embrace new technology, and meet market expectations. The development of such a system is expected to improve farmers' knowledge and, as a result, agricultural output. According to research [8] more than 70% of rural Indians rely on agriculture. They employ Conversational AI, which employs NLP, a subfield of AI that enables computers to perceive, comprehend, and process human languages. The report emphasizes the farming community's resilience in meeting the demands of a growing global population, despite the challenges farmers face as a result of climate change, economic downturns, and environmental concerns affecting soil and water quality, weather patterns, and topography. The team developed "Farmers Friend" - a Conversational AI Bot for smart agriculture - to provide timely advice on various aspects of farming and market scenarios. This bot could improve the researchers' previous Smart Agriculture System based on IoT (SASI). The research [9] introduces an Agro direct selling software with a voice-based Chatbot to assist agriculturists and link farmers with retailers. The application's purpose is to make agricultural transactions more direct and less dependent on middlemen. The app promotes agricultural items such as fruits and vegetables and serves as a repository for farmer data. The main goal is to create a system that connects buyers and sellers so that farmers may sell their commodities directly to consumers in a fair and profitable manner. Through crop tracking, the entire supply chain, from farmers to buyers, can be tracked in real-time. The AI-powered software can also detect diseases in products and audibly transmit that information.

III. METHODOLOGY

The main focus of the research is to improve farmers' agricultural practices by creating a Chatbot. The research is organized into three primary sections. Initially, crop recommendation models based on environmental factors are constructed using ML. The next step is to develop DL models that can use images to detect crop diseases. Finally, a Chatbot is created using natural language processing (NLP). Figure 1 depicts the study work as a block diagram, demonstrating the interrelated flow of these three divisions.

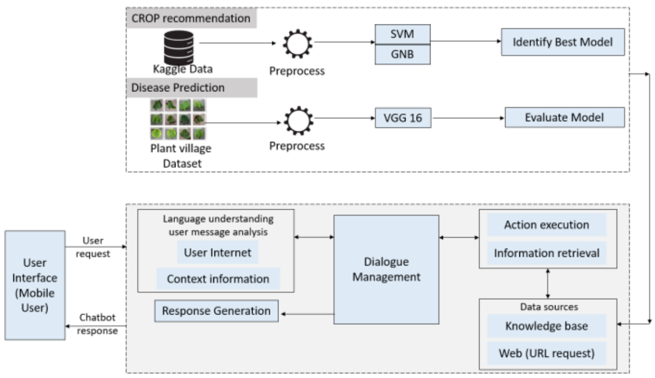

Fig. 1. Block Diagram of AI-powered Chatbots in Agriculture

A. AI Model Development for Crop Suggestion

GNB and SVM are the two ML models utilized for crop suggestion. The 2200 samples, representing 22 different crops, are drawn from a dataset made accessible on Kaggle [10]. The data is split into two sets, one for training and one for testing, with a seven-to-three ratio. Figure 2 depicts a summary of the data from the samples. The following sections go over the SVM and GNB models in detail.

	N	P	K	temperature	humidity	ph	rainfall	label
0	90	42	43	20.879744	82.002744	6.502985	202.935536	rice
1	85	58	41	21.770462	80.319644	7.038096	226.655537	rice
2	60	55	44	23.004459	82.320763	7.840207	263.964248	rice
3	74	35	40	26.491096	80.158363	6.980401	242.864034	rice
4	78	42	42	20.130175	81.604873	7.628473	262.717340	rice

Fig. 2. Crop Recommendation Samples

NAÏVE BAYES: Naive Bayes approaches are used by many supervised learning systems. These employ Bayes' theorem and the naive assumption that each set of features is conditionally independent of the class variable's value [11]. When the dependent feature vectors x_1 through x_n and the class variable y are considered, the following relationship is described using Bayes' theorem:

$$P(y \mid x_1, \dots, x_n) = \frac{P(y)P(x_1, \dots, x_n|y)}{P(x_1,\dots,x_n)} \quad [1]$$

We may simplify the above relationship to to $P(y|x_1, \dots, x_n) = \frac{P(y)\prod_{i=1}^{n}P(x_i|y)}{P(x_1,\dots,x_n)}$ by applying the naive conditional independence assumption, which is $P(x_i|y, x_1, \dots, x_{i-1}, x_{i+1}, \dots, x_n) = P(x_i|y)$ for all i . Because the input has no effect on $P(x_1, \dots, x_n)$, we can use the categorization rule:

$$P(y|x_1, \dots, x_n) \propto P(y)\prod_{i=1}^{n} P(x_i|y) \quad [2]$$

$$\hat{y} = arg\ max_y P(y)\prod_{i=1}^{n} P(x_i|y) \quad [3]$$

$P(y)$ and $P(x_i|y)$ estimate the relative frequency of class y in the training set using Maximum A Posteriori (MAP) estimation. The primary distinction between the various naive Bayes classifiers is the assumptions they make about the distribution of $P(x_i|y)$. Despite their seemingly elementary assumptions, naive Bayes classifiers have proven successful in two real-world applications: document categorization and spam filtering. They are capable of estimating parameters with very minimal training data. In comparison to more complicated algorithms, Naive Bayes learners and classifiers are extremely fast. We may estimate each distribution individually by splitting class conditional feature distributions, allowing us to treat them as one-dimensional distributions and avoid issues caused by the curse of dimensionality. In contrast to the well-known naive Bayes classifier, the GNB technique is used for classification, which assumes that the features have a Gaussian likelihood.

$$P(x_i|y) = \frac{1}{\sqrt{2\pi\sigma_y^2}} exp\left(-\frac{(x_i-\mu_y)^2}{2\sigma_y^2}\right) \quad [4]$$

Through maximum likelihood estimation, the parameters σ_y and μ_y are determined.

SVM: The fundamental purpose of the SVM technique for effective data point categorization is to find a hyperplane in an N-dimensional space (where N is the number of characteristics) [12]. There are several hyperplanes that might be used to divide the data points into two groups. The basic goal is to find a hyperplane with the greatest margin, which reflects the greatest distance between data points of different classes. Increasing this margin to its utmost improves the classifier's ability to consistently categorize subsequent data points. Because they correlate to separate classes on either side of the plane, hyperplanes are ideal decision boundaries for data classification. The size of the hyperplane varies with the number of features input; for example, a line is a hyperplane with two features and a two-dimensional plane with three features. It is difficult to envision hyperplanes when there are more than three attributes.

A support vector is a collection of data points that are close to the hyperplane and influence its orientation and position [13]. Using these support vectors maximizes the classifier's margin; adding or removing support vectors influences the placement of the hyperplane. These vectors are critical when developing the SVM. SVM class identification is based on the output of the linear function; an output greater than 1 indicates one class, whereas an output less than -1 indicates another. SVM employs the interval ($[-1, 1]$) as its adjustment parameters and sets the threshold values to 1 and -1 as a reinforcement margin. The SVM algorithm seeks to maximize the difference between data points and the hyperplane. Hinge loss is the loss function utilized to accomplish this.

$$c(x, y, f(x)) = \begin{cases} 0, & if\ y * f(x) \geq 1 \\ 1 - y * f(x), & else \end{cases} \quad [5]$$

When the sign of the projected value and the actual value are same, the cost is zero. If there is a misalignment, the loss value is calculated. One more thing: the cost function has a regularization parameter. Finding an optimal value for the regularization parameter between maximum margin and minimum loss is its primary goal. Here is how the cost function is changed after the regularization parameter is included:

$$min_w \lambda \left\| w \right\|^2 + \sum_{i=1}^{n}(1 - y_i < x_i, w >)_+ \quad [6]$$

After defining the loss function, the gradients can be determined by computing partial derivatives with respect to the weights. These gradients are then used to update our weights.

$$\frac{\delta}{\delta w_k} \lambda \left\| w \right\|^2 = 2\lambda w_k \quad [7]$$

$$\frac{\delta}{\delta w_k}(1 - y_i < x_i, w >)_+ = \begin{cases} 0, & if\ y_i < x_i, w) \geq 1 \\ -y_i x_{ik}, & else \end{cases} \quad [8]$$

When there is no misclassification, which means our model correctly predicts the data, the only gradient that has to be adjusted is the regularization parameter.

$$w = w - \alpha.(2\lambda w) \quad [9]$$

When our model incorrectly guesses the class of data, we include both the loss and the regularization parameter through the gradient update.

$$w = w + \alpha.(y_i.x_i - 2\lambda w) \quad [10]$$

B. AI Model Development for Disease Identification

The VGG-16 model is used to diagnose crop disease via images. To accomplish this, images of three separate leaves with different diseases on them from the PlantVillage [14] collection are required. Figure 3 shows samples of both unhealthy and healthy images for each crop. The preprocessing procedure includes two major actions: resizing and rescaling.

Fig. 3. PlantVillage Samples

VGG-16: VGG16 is a deep convolutional neural network architecture with 16 layers [15]. It is often used in machine learning competitions and is trained on ImageNet, a dataset containing millions of photos classified into 1000 categories. To begin a transfer learning model, delete the last few entirely connected layers and replace them with the appropriate succeeding layer. The VGG16 model's seven-layer architecture consists of five convolutional layers and two fully connected layers. The input layer handles the raw images before proceeding to the feature extraction layer. The convolutional layer then processes the input by generating new object features through the use of various filters. These features are critical in identifying the best testing method.

$$Output = \frac{n+2p-f}{s} + 1 \qquad [11]$$

Where:

n represents the input height or length.
f denotes the length or height of the kernel filter.
w represents the padding applied.
s signifies the strides used

Following the feature extraction phase, the outputs are delivered to the pooling layer. This layer reduces the dimensions of large-sized image objects by minimizing parameters while maintaining critical information. Its primary function is to keep the highest value in **each** layer. It is important to note the lack of weight values in this layer. Pooling is classified into two types: MaxPooling and global average pooling. MaxPooling selects the highest value from the convolution results, whereas global average pooling computes the average value from the convolution results.

$$Outmaxpool = \frac{n-f}{s} + 1 \qquad [12]$$

Finally, it is the fully connected layer's responsibility to accept extensively filtered images and convert them into labels for various categories. This layer leverages inputs obtained from earlier processing results to uncover features that are connected or correlated with other classes. The goal of this layer is to combine all nodes into a single dimension.

$$Z_j = \sum_{j=1}^{c} w_{i,j}^T X_i + b_j \qquad [13]$$

Where:

Z_j represents the network's output value
X_i denotes the input result from feature extraction
$W_{i,j}$ signifies the network weight
i corresponds to the total input features
j signifies the total target classes
b_j denotes bias

C. Chatbot Creation

Many approaches are used to create a Chatbot; developers choose their algorithms, platforms, and tools based on the nature and intended application of the Chatbot. This will assist both the developers working on the Chatbot and the end users. When creating a Chatbot, bear the following things in mind: how to accurately represent information; how to create answers; and what to do if the bot misunderstands the user's remarks. The initial step in developing the system is to adopt a modular development method to break it down into its component parts.

- Begin by saying "HI". The Chatbot interaction process begins when a question is posed via a messaging tool such as Facebook, WhatsApp, Slack, Skype, or WeChat or a text/speech input app such as Amazon Echo. The Language Understanding Component analyzes a user's request to determine what they want and any relevant information (such as "translate" and "environment").
- After processing the user's request, the Chatbot decides on the next step. This could include acting quickly in light of new information, preserving knowledge for later use, seeking further context, or asking for clarification.
- After understanding the request, the Chatbot takes action and gets information. When a user asks the Chatbot to do something, it either does it itself or obtains the information it requires from its knowledge base, which could be a database or other external resources accessed via API queries. The knowledge base employs ML and DL models to enable the Chatbot to respond to user requests, particularly those concerning agriculture.
- After data retrieval, the response Generation Component considers the user's intent and context information to construct a human-like answer using Natural Language Generation (NLG). Rule-based models can be used to produce appropriate responses.
- A Dialogue Management Component's primary job is to continuously update the discussion context, which comprises the current intent, identified entities, and any missing entities required to satisfy user requests. Because of this all-encompassing strategy, the Chatbot and user will have a fruitful and continuous interaction.

IV. EXPERIMENTAL OUTCOME

The results of experimentation from all three stages of the investigation are presented in detail here. In terms of accuracy, precision, and recall, GNB surpasses SVM in the domain of crop suggestions. GNB achieves impressive accuracy, precision, and recall scores of 0.991, 0.972, and 0.975. Figure 4 presents a comprehensive visual representation of this comparison by using a bar chart to highlight the relative performance of the two ML models.

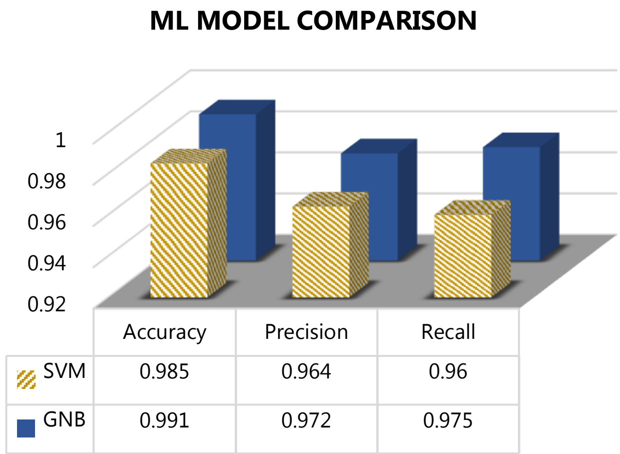

Fig. 4. Performance of ML models on crop suggestion

The VGG-16 model for agricultural disease identification is evaluated using accuracy and loss metrics. Figures 5 and 6 show the model's performance in terms of accuracy and loss during the validation and training stages. The VGG-16 model's extraordinary accuracy in detecting crop diseases is clear from its outstanding values of 0.98 and 1.00 during the validation and training stages, respectively.

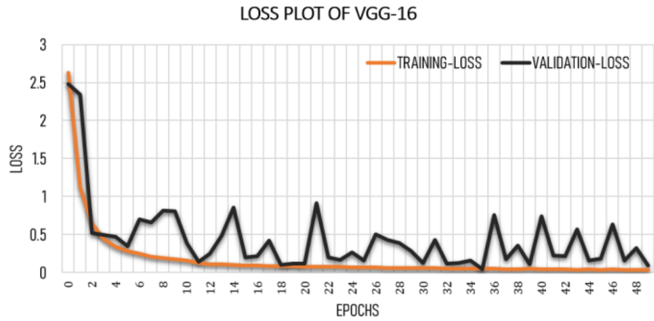

Fig. 5. VGG-16 Loss Performance

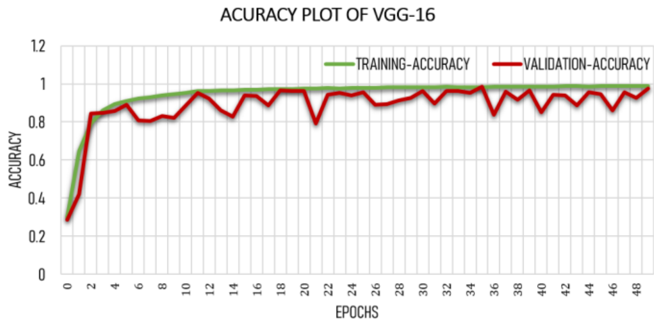

Fig. 6. VGG-16 Accuracy Performance

The final stage of the study is creating a Chatbot and updating the Chatbot's knowledge base using data from both GNB and VGG-16 models for crop suggestion and disease identification. Figure 7 depicts how the Chatbot works. Figure 7.a depicts the Chatbot's response to farmers' crop requests, demonstrating its ability to provide relevant recommendations. Figure 7.b shows how the Chatbot can diagnose diseases and provide critical information to farmers. These types of screenshots demonstrate the practical implementation of the research.

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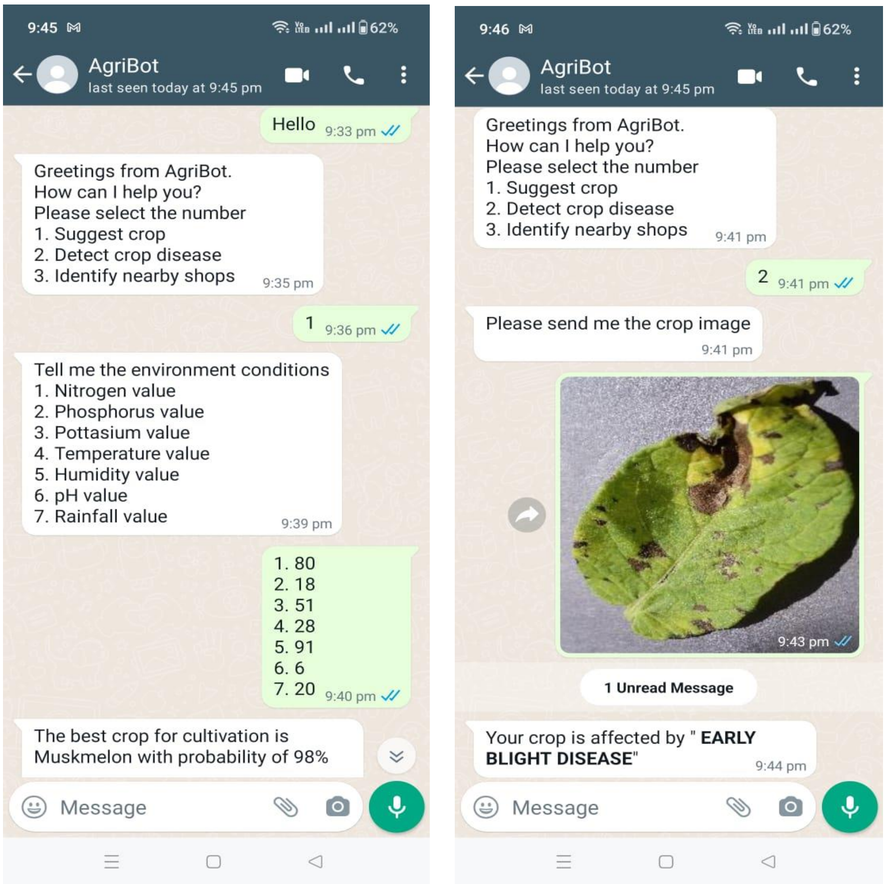

a) b)

Fig. 7. Working of AI-powered Chatbot in Agriculture

V. Conclusion

Farmers face a wide range of issues, including ineffective irrigation systems, weed management, and the challenges of plant monitoring due to internal and external factors. However, there is potential for enhancing performance and resolving these issues through technology integration. Several AI-driven approaches stand out as interesting options.

This study demonstrates a conversational chatbot that employs AI to mimic humans and respond to queries raised by the farmers. The chatbot collaborates with two models to give farmers a comprehensive solution: the VGG-16 model for disease prediction and the GNB model for crop suggestions.

As previously said, the testing results demonstrate how well the chatbot performs in terms of providing meaningful information. It should be noted that the current chatbot version has a limitation in that farmers must manually enter environmental data. To address this issue, in the future, sensors can be integrated with the chatbot so that environmental factors may be recorded automatically. This update is a significant step towards achieving efficient farming and precise agriculture.

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