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Cloud-Based Outreach and Extension Decision Support System Using Machine Learning Models

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Abstract: The Cloud-Based Outreach and Extension Decision Support System uses machine learning models to enhance outreach and extension initiatives by providing accurate predictions on the expected impacts of programs on stakeholders. The system operates on a cloud-based infrastructure, allowing for flexibility in data storage and convenient access to information from various locations. The integration of machine learning models allows for the analysis of historical data and the generation of accurate forecasts, empowering decision-makers to make informed choices regarding outreach and extension activities. Furthermore, the system design makes use of web technologies to offer a user-friendly and secure platform for outreach and extension decision support. Users, including the institution and the community, may safely access the system using a web browser using the Secure Sockets Layer. The system represents a significant step forward in optimizing outreach and extension efforts, enhancing stakeholder impact, and fostering a more responsive and adaptive approach to community engagement. Moreover, the Random Forest Decision Tree classification, the main learning algorithm used in the study, is combined with test results and training data to predict which outreach program and extension would be most appropriate for the chosen Laguna University community.

Keywords: *Cloud-based, Decision Tree, DSS, Machine Learning, Predictive Model, RF.*

1. Introduction

The complexity of running an organization on a worldwide scale has multiplied immensely. Corporate or organizational decision-making cannot meet the needs of global demands if people solely depend on human agency. Relying only on one tool, piece of equipment, or human may still lead to mistakes in analysis and judgment. The literature regularly refers to a lack of strategy and worker skills. The high level of investment that is required for a complex decision, as well as the impression of high risks with uncertain future returns, can potentially be averted by using decision support systems that can fulfill these criteria while also delivering fact-based support [1].

The recent growth of decision-making by machine learning, also known as AI algorithms, presents a new set of obstacles to this age-old topic, despite the fact that the difficulties of building decision-making systems including human actors are firmly established. Artificial intelligence technology and, in particular, machine learning algorithms make it possible to generate new knowledge and predictions from data by synthesizing strong patterns from massive data sets. One of the main motivating factors for the recent growth of advancements in machine learning is the prospect of making decisions swiftly, precisely, reliably, and inexpensively on track with the intellect of humans. When it comes to making significant decisions, professionals in numerous fields, including transportation, agriculture, human resource management, research, finance, government affairs, and legal guidance, are increasingly turning to the advice of algorithms based on machine learning for support. The evolution of decision support systems has led to a reduction in the human burden associated with analyzing organizational data. Decisions may be made swiftly based on the data at hand, which might lead to rapid quality gains for the business. Because data quality dictates an organization's quality, a choice might be made at a precise time, diverting development onto the right track. Decision support systems may choose as well as assess data to identify patterns and formulate plans and solutions. In most cases, this decision-making aid has been integrated into regular operations [2].

1.1. Objectives of the Study

The general objective of this study is to identify the outreach and extension program with a decision support system using machine learning models for the adopted community of Laguna University.

In line with this, the project aims to achieve the following specific objectives:

1. To develop a decision support system model using Random Forest decision tree algorithm with community profiling for identifying the best and fitted outreach and extension program for the adopted community.

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2. To analyze the machine learning model used in the development of the system.
3. To validate the model used in the decision tree algorithm for decision support system.
4. To implement an outreach and extension decision support system with machine learning models on a cloud-based platform.

1.2. Scope and Limitation

The study covers the decision support system with machine learning models in terms of identifying the best outreach and extension programs for the community. A Random Forest decision tree algorithm model will be used that will show the suggested program to be implemented based on the data sets. This study will present data such as community demographics. Using the Random Forest decision tree algorithm, it will find the best activities or programs to be implemented in a certain community that best fit the data.

This study does not cover any new developments in machine learning models to show the effectiveness of the programs implemented in the community. The implementation of a cloud-based platform for outreach and extension programs in the Python programming language will be used.

2. Related Literature

An indication of how accurate the predictions made by the decision support system, which utilized a machine learning model using the random forest decision tree algorithm, were may be found by reviewing and studying the preliminary literature that is currently available. On the other hand, the aforementioned research considered several kinds of additional algorithms connected to predicting outcomes. This literature review had several purposes, but one of the primary ones was to emphasize the role of decision support systems as the ideal solution for determining the best activities or programs to be implemented in the adopted community of Laguna University that most effectively match the data. There are numerous reasons why this was one of the major goals of this research study. The researchers wanted to analyze the literature in this field in order to discover every study that used decision support systems to construct a machine learning model on a cloud-based platform.

The literature review highlights the importance of decision support systems in enhancing resource allocation and offering insightful information for decision-making. The use of decision trees and other machine learning algorithms inside a cloud-based platform has the potential to improve accuracy and scalability. The examined research bolsters the idea that decision support systems may improve decision-making processes in a variety of contexts, including the adopted community of Laguna University, when they are linked with machine learning models and cloud-based platforms.

The reviewed literature covers a wide variety of subjects and industries, including agriculture, cloud computing, facility maintenance, healthcare, and supply chain management. Each research provides distinctive insights and contributions particular to each field. As an example, [3] show how a web-based serious gaming application might enhance cross-jurisdictional cooperation in water hazard reduction. The advantages of predictive maintenance planning employing data-driven strategies and machine learning algorithms in facility maintenance management are highlighted by [4]. In the framework of the fourth industrial revolution, [5] talk about the developments in predictive maintenance approaches as well as their difficulties. [6] investigate the effects of computerized clinical decision support systems (CDSS) on healthcare professionals, patients, and the whole healthcare system. They explore the many forms, efficacy, and possible hazards related to CDSS and provide ideas for enhancing the CDSS procedure that are supported by data. According to [7], community policing software systems must adhere to legislation and be developed with security in mind. They also stress the need of data protection and privacy. Decision support systems are also essential for tackling security issues in cloud computing. In their proposal of an improved intrusion detection and classification (EIDC) system based on machine learning techniques, [8] provide evidence of the system's efficiency in identifying and classifying network traffic in cloud settings.

The literature review also indicates the obstacles and developments in machine learning (ML) and artificial intelligence (AI) as they apply to decision-making processes. The findings emphasize the need for suitable decision-making models that may successfully combine AI and ML approaches. Decision support systems may use real-time data and scalable processing capacity by using cloud-based platforms and IoT devices, enabling quicker and more accurate decision-making across a variety of areas. These results highlight the opportunity to encourage innovation and enhance decision outcomes by incorporating new technology into decision support systems.

3. Research Methodology

3.1. Software Design

In the outreach program and extension services is a critical determinant of an institution and community's success. In response to the growing need for efficient, transparent, and data-driven decision support system, the research propose a comprehensive decision support system designed to cater to the requirements of both the institution and community.

The system is accessible through a computer-based application interface, allowing the institution and community to engage with it from any location, leveraging the convenience of web accessibility. Furthermore, paramount to the system design is the emphasis on data security and privacy. To ensure the confidentiality of sensitive information and the integrity of data transfers. Secure Sockets Layer (SSL) or its modern counterpart, Transport Layer Security (TLS) are implemented, for secure data transmission.

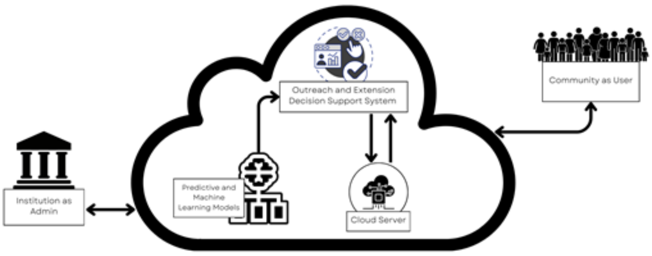


Fig. 1. Cloud Based Outreach and Extension Decision Support System Using Machine Learning Models Software Design.

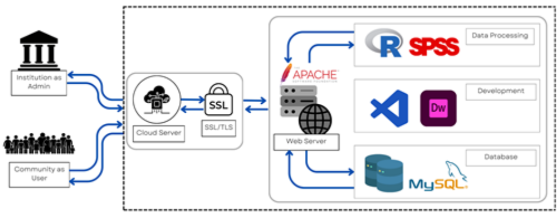
The system design makes use of web technologies to offer a user-friendly and secure platform for outreach and extension decision support. Users, including the institution and the community, may safely access the system using a web browser using SSL. With its file system and MySQL database, the web server manages user requests, processes data, and offers the required information or functionality. This architecture offers an organized and safe method of managing the decision-making process.

3.2. Conceptual Design

Certain processes, needs, and concepts were explored at length in order to envision the design and development of the project, which would hopefully lead to the intended results of this research. Long periods of discussion and brainstorming eventually led to a single, widely supported idea.

The figure 2 below presents the conceptual framework for the research. The input, processing, and output are the three main sections that the figure 2 addresses.

In the input phase, the institution plays the role of administrator, while the community takes on the role of user. Incorporating cloud-based decision support and machine learning models into the system are both part of the process phase. The last phase is a cloud-based, machine learning-powered decision assistance system for outreach and extension.



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3.3. System Architecture

In order to facilitate rapid innovation, flexibility in resources, and economies of scale, cloud computing involves transmitting various computer services via the Internet, often referred to as the cloud. Such services include storage, networking, analytics, software, servers, and intelligence. Users may save operating costs, improve infrastructure management, and adapt to changing business demands by paying only for the cloud services they really utilize. A major shift in how most companies see their information technology resources has occurred with the advent of cloud computing.

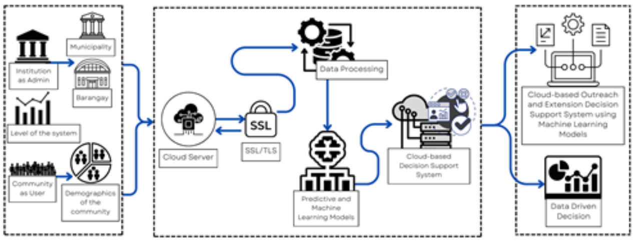

Fig. 3. System's Architecture of the Proposed System.

Figure 3 depicts the separation of admin and user roles on a cloud server hosting the outreach and extension decision support system. The community itself will act as the system's user, connecting to the server and selecting the information they want to see. In essence, they may see their demographic profile and provide supporting documentation. However, the institution will act as the system's administrator, and it will be able to validate community members' submitted documents. The administrator gets access to the verified demographic profile of the community, created with the help of predictive and machine learning models, which will inform the selection of the most beneficial outreach programs and extension services.

3.4. Input and Output Reports and Analysis

The processes of the extraction and evaluation of data or reports and analysis include searching through a tremendous amount of data databases in order to identify information that is implicit but may still be of use. The transformation of data is one of the processes that enables the discovery of new knowledge. Other processes that support the discovery of new knowledge include the acquisition of target data and the processing of facts for a specific purpose.

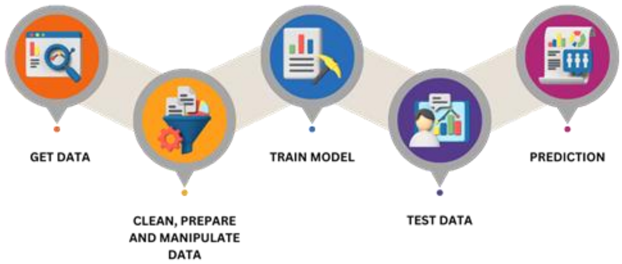

Fig. 4. Predictive Model.

As can be seen in Figure 4, this procedure required the elimination of noise and outlier findings in order to establish trends and patterns and ultimately lead to the acquisition of the right information and decision.

3.5. Algorithm Used

The Random Forest (RF) is the algorithm used and is an example of an ensemble learning technique. Based on data samples obtained from the training set, it generates a large number of limited, independently associated decision tree predictive factors, as illustrated in Figure 4 above. The idea is that through the accumulation of vulnerable learners, one can cultivate an adequate capacity for acquisition.

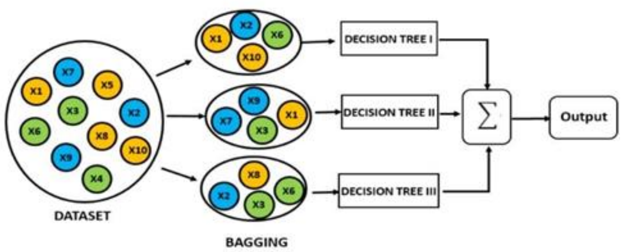

Fig. 5. Random Forest Algorithm Overview.

As can be seen in Figures 4 and 5, the Random Forest algorithm constructed decision trees using gathered samples from the training set. This was done a variety of times, with B being the target number of trees for the forest.

In order for a tree to develop, its central node has to be chosen from among several asymmetrical subsets of the peaks. Averaging the results of each generated tree ensured that the final forecast from a random forest would have low inclination and change, even when the exhibition of randomness led to a rising tendency toward expectation.

3.6. Software Development Methodology

To create systems in a way that prioritizes the needs of the end user, agile modeling is at the forefront of innovation. An approach to software development based on a shared set of values, principles, and fundamental procedures is also known as the agile methodology. An iterative and incremental approach is the foundation of agile software development. Agile methods, in contrast to traditional ones, do not need as much forward planning and may easily adapt to evolving needs and ongoing customer input [9].

Following the notion of the Agile Development Life Cycle model, the researchers will utilize the project development approach for this study to lead the researchers through the step-by-step process of constructing a system via analysis and design.

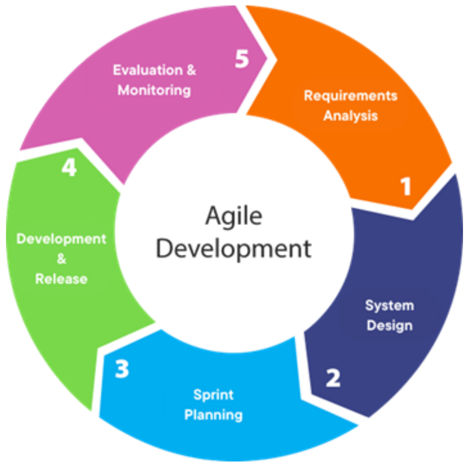

Fig. 6. Agile for Software Development Methodology.

At this juncture in the requirements analysis process, it is essential for the institution to convene as the administrator and for the community to gather as the users. Through user interviews, the researchers will gain insight into the potential future uses of the system. It is critical that these requirements be specific, measurable, and all-encompassing. The present system's design is based on the requirements gathered in the first stage; the second phase is system development. In order to find the answer, scientists will first come up with a plan for how to proceed. Researchers will use the institution's specifications to determine which components the system must include in the sprint planning phase after determining the concept's viability. Iteratively breaking down the system's various components into smaller, more manageable chunks is the next step for the researchers. Planning for deployment iterations and developing and testing system features are both responsibilities of the development and release phase, which is the fourth stage of the project life cycle. Researchers start with iteration 0, since no features are provided at the beginning of development. After development is complete, the system will undergo testing to guarantee it satisfies all requirements. After testing and installation at the institution's location, the system will be ready for use. The final step is evaluation and monitoring, during which the built system will be examined and tracked in real-time at the institution. Once users start using the system, the researchers might find more issues that need fixing.

4. Results and Discussion

A comprehensive analysis of the outcomes derived from the data analytics model, random forest, and Cloud-Based Outreach and Extensions Decision Support System is discussed in this section. The findings obtained from the prediction model and validation approach used in the research are showcased

Table 1. Likert Scale with Acceptability Level

Statements	Weighted Mean	Verbal Interpretation
1. Functional Suitability	4.87	Strongly Agree
2. Performance Efficiency	4.82	Strongly Agree
3. Usability	4.84	Strongly Agree
4. Reliability	4.86	Strongly Agree
5. Security	4.81	Strongly Agree
6. Maintainability	4.87	Strongly Agree
Overall Weighted Mean	4.85	Strongly Agree

The general evaluation of respondents indicates that security earned the lowest weighted mean of 4.81 and a verbal interpretation of "Strongly Agree," yet the system may still be regarded as reliable because of the amount of score it obtained. Nevertheless, the functional suitability and maintainability requirements received the highest weighted mean score of 4.87 and a descriptive equivalent of "Strongly Agree," indicating that the Cloud-based Outreach and Extension Decision Support System using Machine Learning Models has met the essential purpose that it requires and can adapt well to changes in its environment or with its requirements. The overall weighted mean of the requirement specification standards is 4.85, with a verbal interpretation of "Strongly Agree" as well as the sense that the researcher's study satisfies the standards and quality characteristics.

4.1. Prediction and Validation

The test results and training data would be utilized in conjunction with the Random Forest Decision Tree classification, which serves as the primary learning algorithm employed in this endeavor, to forecast the most suitable outreach program and extension for the selected community of Laguna University. Within this domain, the analyst illustrates the diverse metrics employed to evaluate the viability and performance of the classifier model. By comparing the observed accuracy to a predicted rate of accuracy that probably corresponds to the confusion matrix and by evaluating the reliability and credibility of the sources, numerous trials were used to validate the accuracy of the generated test. In the metrics presented in Table 7 for assessing interrater reliability, the classifier can also be evaluated using precision, recall, and F1-score [10].

Table 2. Value and Level of Agreement

Kappa Value	Level of Agreement
0-.20	None
.21-.39	Minimal
.40-.59	Weak
.60-.79	Moderate
.80-.90	Strong
Above .90	Almost Perfect

4.2. Measure and Analysis

In order to evaluate the model's precision, the researchers use the classification matrix constructed from the training data. In order to categorize all cases generated by the model, a classification matrix compares the predicted and actual values. The sums of the counts for each category's cases are subsequently presented in the matrix. The classification matrix, also known as a confusion matrix, is a conventional instrument utilized in the assessment of statistical models [11].

Predictions are made using predicted probabilities from the model and a specified probability threshold (usually, but not always, 0.50). The confusion matrix, or classification table, comprises a cross-validation of observations by predicted labels or groups. In the case that the input of events and trials has been used, the labels on the categories will always reflect events and non-events rather than the precise values of a target variable. Two compartments aligned along the primary diagonal display the number of accurate predictions [12].

Table 3. Confusion Matrix

	Predicted Positives	Predicted Negatives
Actual Positive Instances	Count of True Positive Instances (TP)	Count of False Negative Instances (FN)
Actual Negative Instances	Count of False Positive Instances (FP)	Count of True Negative Instances (TN)

The effectiveness of the random forest algorithm that will be implemented to the outreach and community extension services will be evaluated based on accuracy. Precision refers to the rate at which the system of classification holds up. By definition, when the accuracy is one hundred percent, the anticipated and actual cases are similar.

Table 4. General evaluation of respondents in the Cloud-based Outreach and Extension Decision Support System using Machine Learning Models

Statements	Weighted Mean	Verbal Interpretation
Confusion Matrix Analysis	4.50	Strongly Agree
Performance Metrics	4.75	Strongly Agree
Interpretation of Kappa Value	4.66	Strongly Agree
Overall Weighted Mean	4.64	Strongly Agree

The general expert review of the system algorithm indicates that Confusion Matrix Analysis earned the lowest weighted mean of 4.50 and a verbal interpretation of " Strongly Agree," However, the calculation may still be regarded as accurate due to the quantity of points it received. Nonetheless, the Performance Metrics obtained the highest weighted mean score of 4.75 and a descriptive equivalent of "Strongly Agree," indicating that the system is maintainable and that the fault in the Cloud-based Outreach and Extension Decision Support System using Machine Learning Models can be identified and fixed. The overall weighted mean of the requirement specification standards is 4.64, with a verbal interpretation of "Strongly Agree" and the notion that the researcher's study meets the system standards and quality characteristics.

4.3. Random Forest

For the purpose of evaluating various comparison metrics, a summary of the model's performance on a testing dataset was provided in this section. The decision tree, which implements the random forest (RF) algorithm, is the initial option. Algorithm RF, which Leo Breiman and Adele Cutler jointly developed, is utilized in decision tree learning to construct a decision tree from a given dataset.

Similar evaluation and consideration are devoted to the decision tree algorithm, which is implemented for classification and regression. Input for both cases comprises the nearest instances of function training. By learning simple decision principles that are deduced from historical data, known as "training data," the outcome is contingent upon whether the decision tree algorithm is employed to rank or regress. A form of computation known as machine learning models enables programming programs to predict outcomes with greater precision without requiring explicit modification.

Table 5. Random Forest Decision Tree Classifier Result

Classification	No. of Sample	Correctness in Percentage
Correct	401	98.74%
Incorrect	5	1.23%

The outcome presented in Table 5 for the Random Forest Decision Tree Classifier merely illustrates the precision of the gathered samples. Out of a total of 406 samples collected, 401 achieved an accuracy of nearly 98.74%. Out of the 406 samples collected, only five samples, or 1.23%, were classified incorrectly. This would result in an increased level of confidence or significance when formulating a prediction.

The confusion matrix, which is a product of the cross-validation prediction, also played a role in preserving this reputation. As shown in Table 10, the diagonal entries in the confusion matrix indicate correctly classified samples, while the remaining entries represent misclassifications. This capability allowed the researchers to visually represent prediction outcomes and associated derived statistics from the data on a class-by-class basis.

Table 6. Confusion Matrix Generated by Random Forest Decision Tree

		Actual		
		a	b	Classification Overall
Predicted	A	392	2	394
	B	3	9	12
	Truth Overall	395	11	406

Performance metrics considered including precision, recall, specificity, f1-score, and Kappa Value. The result is shown in Table 7 below:

Table 7. Performance Metrics Comparison by Random Forest Decision Tree

Performance Metrics	RF
Precision	0.994
Recall	0.992
Specificity	0.818
F1-Score	0.992
Kappa Value	0.776

As the result shown in Table 7, Random Forest (RF) achieved a precision of 0.994, reached recall of 0.992, a specificity of 0.818, and Kappa Value of 0.0776 respectively. The above values mean how high the performance of a classifier in terms of individual metrices and how close it is to a 100% accuracy or perfection. In this case, RF classifier performance is relatively high in almost all of the different metrics such as precision, recall, specificity, f1-score, and Kappa value.

The construction of the decision tree is accomplished through the use of recursive binary splitting with the initial predictor set. At the outset, the construction of the tree to its utmost extent is completed. The model of node divisions in the full-size tree was intricate. Next, it is crucial to prevent the tree from being overfitted with excessive variance and complexity. To achieve this, cross-validation techniques are utilized to identify the optimal divisions of the tree, which are then utilized to reduce the size of the tree to that extent. The TP, FP, precision, recall, and F1-score variables are used to assess accuracy.

5. Conclusion

To develop a decision support system model using Random Forest decision tree algorithm with community profiling for identifying the best and fitted outreach and extension program for the adopted community. Prior to implementing the RF Decision Tree, the researchers must first carry out the Data Collection and Preparation stage, which includes obtaining relevant data on the community, such as demographics and other aspects that may impact the outreach and extension program. Make certain that the data has been appropriately processed and presented for analysis. Furthermore, the decision support system model is built utilizing the Random Forest decision tree method, which is a machine learning approach. Based on data samples from the training set, this method builds a huge number of shallow decision trees. Following that, community profiling is included in the model to understand the particular requirements and features of the chosen community. This profile may aid in determining the most effective and suitable outreach and extension program for implementation. Following that, the data training process is examined and verified in the decision support system using the machine learning model. To assure the model's correctness and dependability, evaluate its performance using relevant metrics and approaches. Following the removal of noise and outlier findings Creating trends and patterns, as well as gathering information. A 70% training set will be seen in the train model using the RF Decision Tree. The remaining 30% will be formed as a test sample using the RF Decision Tree. The aforementioned training data and test results are utilized to anticipate the appropriate outreach and extension programs, with people's views and opinions classified as "Strongly Agree," "Agree," "Neither/Nor Agree," "Disagree," and "Strongly Disagree." The decision support system's implementation on a cloud-based platform provides for easy accessibility and adaptability, making it more efficient and effective in assisting decision-making processes.

To analyze the machine learning model used in the development of the system. Analysis of the machine learning model implemented in the system's development commences with the accumulation of data. Community demographics, outreach and extension program data, and other pertinent information are collected to train the machine learning model. Using assessment criteria such as accuracy, precision, recall, and F1-score to evaluate the effectiveness of the machine learning model. The accuracy of the model's ability to forecast the most effective community outreach and extension initiatives will be evaluated with the support of this information. The relevance of individual features or variables in the machine learning model is then determined. Methods such as feature importance ranking and permutation importance shall be employed to accomplish this. Additionally, model interpretation will take place in order to get an understanding of the manner in which the machine learning model is generating predictions. Techniques such as feature significance analysis and partial dependency plots may help with this. Moreover, the effectiveness of the suggested outreach and extension programs can be assessed by employing a validation dataset to compare the predictions of the machine learning model with actual outcomes, thereby validating the model's accuracy.

To validate the model used in the decision tree algorithm for decision support system. The researchers utilized cross-validation techniques to verify the model used in the decision tree algorithm for the decision support system. These techniques help identify the optimal divisions of the decision tree and prevent excessive fitting. The researchers were able to test the reliability of the model and confirm its efficacy in predicting outcomes by utilizing cross-validation. The precision, recall, and F1-score variables were used to assess the model's accuracy.

To implement an outreach and extension decision support system with machine learning models on a cloud-based platform. In order to implement a machine learning-driven outreach and extension decision support system on a cloud-based platform, the research indicates using the Random Forest decision tree algorithm. Based on the data sets, this algorithm will do an analysis of the demographics of the community and provide recommendations for the activities or programs that would be most beneficial to execute in a certain community. Users will be able to use the system from any place as long as they have an internet connection. The system will be developed using the Python programming language, and it will be available by means of a cloud server. Secure Sockets Layer (SSL) or Transport Layer Security (TLS) will be used by the system in order to encrypt data while it is being sent. This will, therefore, guarantee the safety of the data. The component of the system known as the web server will be responsible for handling user requests, processing those requests, and sending results. Ultimately, the purpose of this solution is to provide a platform that is accessible in the cloud and makes use of machine learning models to assist with decision-making processes for outreach and extension programs in the chosen community.

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