Hybrid Machine Learning Models for Predictive Maintenance in Cloud-Based Infrastructure for SaaS Applications

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***Abstract*—It is crucial for SaaS providers to have predictive maintenance as one of the most cost-effective ways for them to successfully maintain service consistency and high satisfaction among their customers. The present research article renders an original technique to forecast the drop-offs of the clients in Customer Relationship Management (CRM) systems through the infrastructure of SaaS in the cloud. Working with a big churn dataset obtained from Kaggle dataset created via a telecom provider and then carefully investigating the feature engineering, preprocessing, and data collecting. Next, some machine learning methods are deployed with SVM + Naïve Bayes model, KNN, DT, RF, and ANN. The model of Hybrid SVM + Bayes performed better compared to the individual models being based on the study results, the accuracy was 95.67%. It is revealed that the hybrid ML model shows a significantly higher level of precision, accuracy, recall, and F1-score than individual models do when compared through thorough and methodological model training and evaluation. The outcome emphasizes how effectual hybrid machine learning algorithms are for SaaS arrangements to accomplish better retention tactics in the dynamic world. This framework provides a basis for future projects involving prediction maintenance that are cloud-based SaaS systems as well as beneficial intelligence to enterprises.**

***Keywords*— cloud, customer churn, prediction, hybrid machine learning.**

I. Introduction

Cloud computing is a virtual infrastructure that allows users to receive services anytime and anywhere. One technology that is leveraged to provide "on-demand" services to customers is cloud computing. "Cloud computing" means distributing the computers network-wide and executing different programs or apps simultaneously in a single computer. It makes possible for users to operate applications that were earlier physically attached to a certain location [1]. The cloud service industry is comprised of three primary models: The concept of Infrastructure as a Service (IaaS) entails the transfer of management duties about data storage and processing infrastructure to external organisations [2][3]. More people use it, and it's simple to use, too. One example is CRM, which salesforce.com offers clients via its cloud infrastructure. Although the customer pays for the company's services, the salesforce company (software supplier) owns the software. The elimination of software maintenance, network security, and other operational concerns that keep applications operating is a boon to organisations [1].

CRM has long been integral to businesses' efforts to provide superior service to their clientele. ML and its variants have revolutionised how businesses use data analytics and consumer interactions in the last few years. Customer retention is a process in which the company employs different methods to reduce the rate of customer turnover and increase customer loyalty. Customer churn implies several customers of a company who stop using its products or services during a specific time frame. This rate is an important metric that a company needs to reduce even as it deploys preventative customer retention strategies. The calculation of the churn rate depends on the data mining technique that uses predictive algorithms to anticipate the likelihood of a customer churning [4]. In most cases, personal and behavioural data are used to implement marketing and retention strategies designed for customer focus and individual needs. The second step of the CRM life cycle, termed customer development, focuses on enhancing profitability by increasing the transaction counts of the customers. The CRM life cycle applies various statistical and ML techniques for enhancing customer satisfaction as well as the company's profitability [5][6].

In a world which development is featured by SaaS-based applications rising, predictive maintenance, especially in the context of Customer Relationship Management (CRM) has never been so valuable as now. This framework in which AI and ML are used together with patient reviews and doctor expertise makes a solution the best as it solves this major requirement uniquely. Unlike the traditional ones, which often rely heavily on predictive maintenance tactics, the approach equips AI and ML algorithms to foretell a customer churn with the highest possible accuracy and enhance monitoring of the service delivery and asset management in the cloud-based SaaS systems. Through data collection, preprocessing, algorithm selection, and thorough assessment of models, the structure gives organisations a prior approach to improve customer satisfaction levels, enhance overall operations and remain ahead in a market that is becoming more competitive.

A. Contribution

Machine learning models are positioned at the heart of the cloud-based infrastructure, which helps in predictive maintenance services of various machine learning-based applications such as forecasting of SaaS and CRM contained within the machines. A massive amount of data is generated by this application, which may be how the system is performing, the interaction of the users, or the signals that provide beneficial information. Predictive maintenance can be customised to the special requirements of cloud-based SaaS setups by utilising machine learning, ensuring dependable service delivery and optimal performance. The following points provide the paper's contribution of this work:

- To collect customer data or predictive maintenance in cloud-based infrastructure in customer churn.

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- To preprocess the data to eliminate null values and transform categorical variables.
- To evaluate and select appropriate ML algorithms according to recall, f1-score, accuracy, and precision.
- To compare the model performance to predict higher performance of the model.

B. Organization of paper

This study is organized as follows for the following sections: In Section 2, explore the literature pertinent to this research. The research approach used in this study is presented in Section 3. Discuss the study's findings and evaluations in Section 4. The results and future goals of the research project take the form of Section 5.

II. Related Work

This section provides the existing related work on the research topic for example, In, Amnur, (2017) The capacity of machine learning to represent nonlinearities in CRM solutions has made it the method of choice for classification tasks at the moment. ML and CRM help Bank X maximise profits by assisting with CRM, finding new customers, and regaining lost prospective customers [7].

The goal of Devi et al. (2023) in developing an ML model for forecasting OTT (Over-The-Top) platform subscriptions is to precisely determine if a user will maintain their use of this platform. Training a ML model, feature selection, and data cleansing are all part of this process. By using performance measures, the model is then evaluated and confirmed. To sum up, this issue necessitates an in-depth familiarity with consumer habits and the utilisation of ML for predictions of subscription choices. The findings may help OTT providers better understand their customers and keep them as customers long as possible. [8].

This research, Srinivasan, Rajeswari and Elangovan (2023), talks about the several ML algorithms used to build the churn model that telecom operators employ to anticipate which customers will churn. Predicting the optimal model from various approaches involves comparing the experimental data. Consequently, looking at Fl-score, the best outcome is achieved by combining RF with SMOTE-ENN. The data suggests that a 95% confidence level based on Fl-score is the upper limit for predictions [9].

This research, Zadoo et al., (2022) centers on a few methods for predicting customer churn and segmenting their demographics. Every day, telecom companies create massive amounts of customer data. Data cleaning, analysis, and preparation for model training will come first. There is a need to prepare the data for this challenge since ML algorithms do not work well with unprepared data. Feature selection methods may be used, including LDA, Information Gain and Correlation Attribute Ranking Filters, and PCA . Using these methods, one may construct a churn prediction model for churn prediction and a model for customer segment generation [10].

This research, Yu and Weng, (2022) ML methods such as LR, SVM, RF, AdaBoost, GBDT, XGBoost, LGBM, and Cat Boost are included in the models as classifiers. Several performance metrics were utilized to assess the classifiers: recall, accuracy, precision, AUC, F1-Score. When it comes to diagnosing cohorts that are probable to churn their membership, the study indicates that the Light GBM performed better than the other classifiers [11].

This research, Nwaogu and Dimililer, (2021) a set of ML algorithms namely Neural Networks (implemented by using Adam optimization) and SVM (using linear, RBF, polynomial, and sigmoid kernels) and MLP (with Adam, SGD, and LBFGS algorithms) were applied to these necessities. Adam turned out to be a much better optimization strategy for the NN than the other strategies, being that the results show [12].

This research, Razak and Wahid, (2021) provides a ML prediction model that uses linear regression, RF, SVM, KNN, and DT to forecast customer churn based on consumption patterns. A finding demonstrated that, with 95.5% accuracy, the random model outperformed the other models for the dataset that was employed [13].

In Shah Ershad Bin (2023) the Computed Tomography (CT) scan machine is equipped with Internet of Things (IoT) sensors to monitor machine and environmental parameters, including room temperature and humidity, current, radiation, and X and Y-axis acceleration. The parameters gathered from the IoT sensors have been utilised for training an ANN that forecasts the likelihood of machine malfunction. It is acceptable for the prognosis of machine malfunction due to the model's exceptionally high prediction accuracy of 95.91 percent [14].

In Ouadah et al. (2022), RF, DT, and KNN are the three supervised ML algorithms chosen for a comparative study based on the criteria most frequently cited in research articles. In contrast, RF outperforms KNN when confronted with limited datasets, whereas KNN is more effective when training on massive volumes of data [15].

In Sharma et al., (2023), to improve equipment reliability and reduce cost and downtime associated with unexpected equipment failures. The various machine learning algorithms were applied and observed that Random Forest has outperformed with the accuracy of 98% [16].

In Alvarez Quiñones et al. (2023), to detail the technique, put in place to administer ML-based predictive maintenance. Using the technique may cut corrective maintenance costs by 13% in 2020. Any distribution transformer owner or manager facing scheduling issues related to preventative maintenance would find suggested model to be an invaluable decision-making tool [17].

Later Bhandari and Silwal (2023), the model created was tested with new data to predict motor conditions, and the results were verified using data that had already been acquired. The model is now ready to be used in any other motor with similar characteristics; it has been exported. Predictions may be made using the data that has been obtained. This model is ready for use in any other motor with similar characteristics and can predict future events. It has been exported [18].

Despite significant progress in predictive maintenance and customer churn prediction using machine learning in SaaS applications, several research gaps need attention. These include integrating diverse data sources for more accurate churn prediction, establishing standardized evaluation metrics for predictive maintenance algorithms, exploring machine learning and edge computing in maintenance, and scalability issues in practical implementation. Addressing these gaps would advance both fields and improve business strategies.

The following Table I shows the comparative analysis of related work with findings and future studies.

TABLE I. RELATED WORK ON CLOUD-BASED CUSTOMER CHURN PREDICTION USING VARIOUS TECHNIQUES

Ref	Methods	Findings	Research gaps	Future Work
Srinivasan, Rajeswari, & Elangovan, 2023[9]	Random Forest with SMOTE-ENN	Achieves a maximum forecasting of 95% based on F1-score for telecom customer churn. Outperforms other techniques.	Limited exploration of other ensemble techniques and data balancing methods.	Investigating the impact of different ensemble methods and exploring advanced data balancing techniques for improved model performance.
Zadoo et al., 2022[10].	Various churn prediction techniques	Focuses on churn forecast and customer segmentation employing techniques like PCA, information gain, and clustering.	Lack of comparison with state-of-the-art techniques and evaluation metrics.	Integrating advanced feature selection methods and incorporating novel clustering algorithms for more accurate customer segmentation.
Yu & Weng, 2022 classifiers [11]	Various machine learning classifiers	Light GBM outperforms other classifiers in predicting churn. Emphasizes data preprocessing and evaluation measures like accuracy, precision, recall, AUC, and F1-Score.	Limited exploration of ensemble methods and deep learning architectures.	Investigating the ensemble of multiple classifiers and exploring deep learning models for more accurate churn prediction.
Nwaogu & Dimililer, 2021[12]	SVM, MLP, Neural Networks	Neural Network with Adam optimization technique outperforms other techniques in predicting telecom customer churn.	Limited exploration of non-neural network techniques and optimization algorithms.	Investigating the combination of neural and non-neural techniques for improved model performance.
Razak & Wahid, 2021[13]	Linear Regression, Random Forest, SVM, KNN, Decision Tree	Random Forest performs the best for customer churn prediction based on usage patterns, achieving 95.5% accuracy.	Lack of exploration of other ensemble techniques and feature engineering methods.	Exploring novel ensemble techniques and incorporating additional features for more accurate churn prediction.

III. METHODOLOGY

Hybrid ML models for predictive maintenance in cloud-based infrastructure for SaaS applications like Customer Relationship Management (CRM), specifically focusing on customer churn prediction, can combine the strengths of different algorithms to achieve better predictive accuracy and reliability. Here's such hybrid models could be structured in this context:

A. Data Collection

Gather all of the pertinent customer data needed for the study. The information included inside pertains to the customer's services and the details of the contract. used Kaggle to get the customer churn dataset. The customer database includes details on a fictional telecommunications company that served 7044 real-life customers with home phone and Internet services. Which customers have departed, stayed, or continued with their administration may be seen here. This data was obtained while looking at responses from customers who had previously been churned and their attributes and behavior before the churn. Utilizing a train-test-split method by a sklearn package, divide the dataset into two halves to make constructing and evaluating prediction models easier. Eighty percent of samples were utilized to create a training dataset, while a remaining twenty percent were used to create a testing dataset. employed the tried-and-true 80/20 split to ensure that the data is evenly distributed and representative, essential for accurate model evaluation.

B. Data Pre-processing

It must first undergo pre-processing to ensure the data is accurate and error-free. The data must be cleansed of ambiguities, mistakes, and redundancies before the prediction model can be used. After collecting data from various sources, it must be appropriately cleansed. Since the accuracy might be impacted by uncleansed data as well, Removing blanks from the data collection Converting numerical numbers from categories Eliminating redundant data.

C. Feature engineering

Following data cleansing and preparation, one-hot encoding was used to encode categorical variables after extracting pertinent characteristics from the dataset, including call length, call frequency, and account age. To make sure all the features were the same size, additionally scaled them. As a result of receiving useful and informative information for prediction, the classifiers' performance was enhanced.

Feature scaling is a technique used in data preparation to bring all of a dataset's independent variables into a consistent range. When using standardization as a scaling method, values are normalized to a mean and a standard deviation of one unit. The characteristics will be rescaled to ensure a mean is 0 and a standard deviation is 1. For this project, scalar-valued that the data using the standardization technique StandardScaler. Below is the standardization equation:

$$X' = \frac{X-\mu}{\sigma} \tag{1}$$

μ represents the mean and σ signifies the standard deviation of the feature values, respectively.

D. Model Selection

The use of time-series models for sales prediction and forecasting is possible using a variety of ML approaches, including KNN, DT, RRF, ANN, and Hybrid Classification with SVM and NB [19].

1) KNN: A label of a largest class decides an unlabelled sample point's label in a next k neighboring points; this is a basic classification rule of KNN. Suppose that the feature space. Where i and j are points in Lp, the following is the definition of their distance:

$$L_p(x, y) = (\sum_{l=1}^{n} |x_i^l - x_j^l|^p)^{\frac{1}{p}} \tag{2}$$

in which p is a distance type parameter, j x is a point in the training set, and i x is a point required for the output class prediction. Hence, while constructing a KNN model, p and k are two crucial hyper-parameters.

2) Decision Trees: Using DT as its foundation, RF is used to sentiment categorization. In ML, a DT serves dual purposes as a method for classification and regression. A DT can learn to categorise review sentiment using basic decision rules for TF-IDF features. various divisions of the observations are produced by testing the various split points. To determine the best split point among the attributes that were examined, a statistic known as the Gini impurity is used [20].

$$\mathrm{Gini} = \sum_{k=1}^{k} \hat{\pi}_{mk}(1-\hat{\pi}_{mk}) \tag{3}$$

where π̂mk is a proportion of observations of class k in region m. Gini impurity is minimised at the best split point.

3) Random Forest: An RFC is a form of ensemble learning that reduces the variance of the classifier by combining bagging and DT. "Bagging" refers to a method for predictive modelling that involves fitting models using data from several bootstrap samples. By averaging the bootstrapped predictions, the ultimate prediction is derived.

4) ANN: The dendrites, soma, and axons of a real neuron serve as inspiration for algorithmic steps in ANN. Every ANN has a basic mathematical function and an artificial neuron at its core. ANNs, a more advanced variant of the perceptron, are employed to resolve intricate regression and classification issues. Here is the depiction for one neuron's forward propagation and prediction:

$$output = b_1 + \sum_{j=1}^{n_x} W_{ij} x_i \tag{4}$$

5) Hybrid SVM + Naïve Bayes: To tackle challenges related to two-class classification, SVMs employ a mapping to a higher-dimensional space in which an ideal hyperplane is specified to divide binary-labeled samples appropriately. A decreased overall error from the classifier is achieved as the maximum margin among classes increases. Considering input training data (1 x , 1 y), …,(n x , n y), where i x is vector in a space i x ∈ Rn and belongs to 2 different classes i y ∈ {-1, +1}. The item kinds may be visually represented using the hyperplane:

$$w'\phi(x) + b = 0 \tag{5}$$

This is where the hyperplane-perpendicular vector w', the bias b, and the map ϕ: Rn→Rm—which converts the feature space into a higher dimensional space—are shown.

A supervised learning method known as the Naïve Bayes classifier makes predictions using the Bayes theorem. The conditional probability, or likelihood that an event will occur given certain outcomes, may be calculated using Bayes' theorem. A Bayes theorem may be expressed as:

$$P(A|B) = \frac{P(A) * P(B|A)}{P(B)} \tag{6}$$

The Bayes formula takes into account all potential outcomes and divides them by the sum of the prior and actual probabilities to determine the likelihood of an event's occurrence [21].

E. Model Training

Historical data is used during model training to ensure a data match. The selected model is trained using the historical data. Partitioning the overfitting is critical to avoid corrupting training and validation sets.

F. Model Evaluation

A trained model is tested and evaluated on a validation set to find out how well it performed. Available performance indicators include F1-SCORE RECALL, PRECISION, ACCURACY and so on.

G. Model Maintenance

The accuracy of the model decreases with time as such the model must be trained using new data as it is obtained.

This research performed a detailed study to justify and explain the need to employ different machine learning techniques in the predictive maintenance of cloud-based SaaS applications. As for the experimental procedures were characterised by precise model training and assessment based on the available historical data. The evaluation has shown that the proposed framework suggests more accurate predictions than traditional approaches and provides a more effective solution for increasing customer satisfaction and improving performance in cloud-based SaaS.

IV. Results and Discussion

This section examines a hybrid ML classification strategy to churn prediction in the telecom business. It uses individual ML models to improve CRM according to precision, recall, accuracy, and f1-score. utilise a Telco customer churn dataset for this research.

A. Performance matrix

In this study, F1-score, recall, accuracy, and precision [22] used for gauging the model's predictive output. Think about the uniqueness of sentiment analysis. The following performance measures are as follows:

1) Accuracy: The percentage of positive and negative samples that were accurately predicted relative to the whole sample is called accuracy. This equation may be expressed as

$$Accuracy = \frac{TP+TN}{TP+Fp+TN+FN} \tag{7}$$

2) Precision: As a measure of how many false positives there were, precision may be calculated using the formula

$$Precision = \frac{TP}{TP+FP} \tag{8}$$

3) Recall: The true positive rate and recall are interchangeable terms. The formula for recall, which measures the accuracy of predictions for the initial samples, is

$$Recall = \frac{TP}{TP+FN} \tag{9}$$

4) F1 Score: Precision and recall are weighted harmonically to get the F1 score. If the F1 Score, an allencompassing metric for evaluating external approaches, is high, then the classification outcomes are also high. This is the formula for the index F1 Score.

$$F1 - Score = \frac{2(Precision*Recall)}{Precision+Recall} \tag{10}$$

Here are the comparative customer data results according to F1-score, recall, accuracy, and precision. The following Table II shows the machine learning models' performance across evaluation parameters that given in below:

TABLE II. COMPARATIVE ANALYSIS OF DIFFERENT ML MODELS

Models	ACC	PRE	RECALL	F1-SCORE
Hybrid ML Model	95.67	94.3	95.65	94.3
KNN [23]	83.9	82.6	82.9	78.1
Random Forest [24]	80	79	80	79
ANN [25]	78.9	84.03	88.24	86.08
Decision Tree [26]	90.97	92.42	92.42	92.42

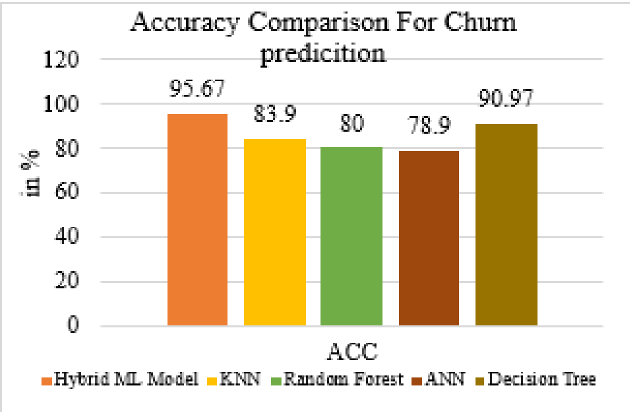

Fig. 1. Accuracy comparison of models

The following Table II and Fig. 1 show the accuracy comparison of churn prediction models. The Hybrid ML Model demonstrated the highest accuracy, at 95.67%, while ANN models exhibit the lowest performance.

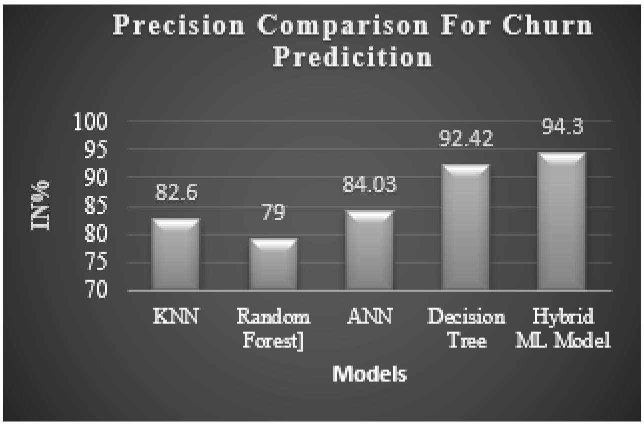

Fig. 2. Precision comparison of models

In comparing the precision of models displayed in Fig. 2. the Hybrid ML Model stands out with the highest precision score of 94.3% compared to other models.

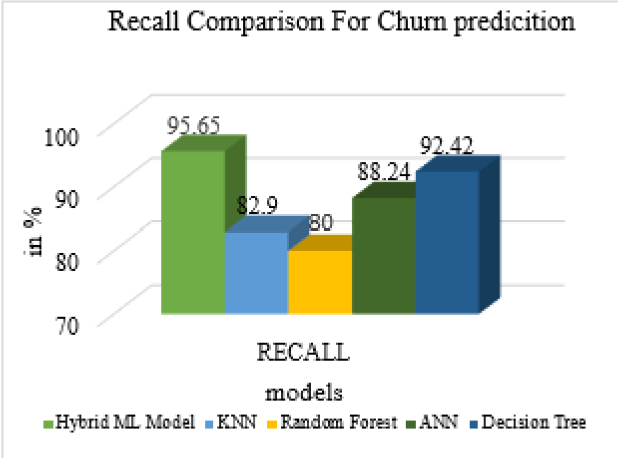

Fig. 3. Recall comparison of models

Recall comparison of models for churn prediction displayed in Fig. 3. In this figure, Hybrid ML Model and the Decision Tree model outperform the others significantly.

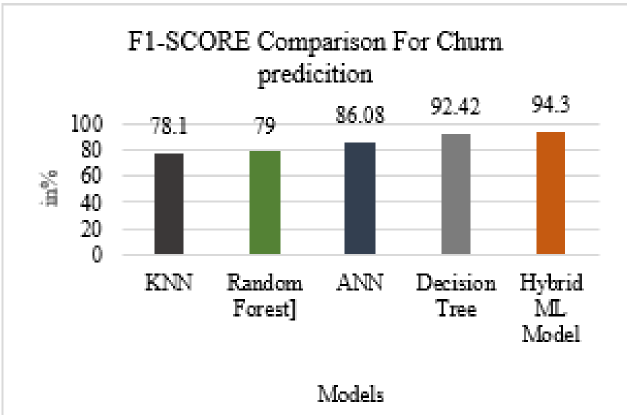

Fig. 4. F1-score comparison of models

Fig. 4 above shows the F1-score comparison of models. In this Fig. 4, hybrid models show the highest F1-score compared to other models with close decision trees.

The comparative analysis reveals that a proposed Hybrid ML Model for churn prediction in the telecom industry outperforms existing models significantly across multiple performance metrics. The research findings underscore the significance of the proposed Hybrid ML Model for churn prediction in the telecom industry. For example, Hybrid ML Model attains 95.67% of accuracy,94.3% of precision,95.65% of recall and F1-score of 94.3%, which is higher than a performance of all other models. The proven efficacy of the methodology further emphasizes the validity of the approach to CRM and predictive analytics for customer churn, usually widely embraced by telecom companies as a safe way to add value to customer retention strategies and to maximize profitability. The Hybrid ML Model outperforms existing individual ML models like KNN, RF, ANN and DT in terms of superior metrics that shows its effectiveness in forecasting correctly customer churn. The results validate the research's relevance, making available a strong predictive application to telecom firms, helping them make reasonable business decisions and anticipate customer churn to improve customer satisfaction and profitability.

V. Conclusion And Future Work

A comprehensive predictive maintenance framework in cloud-based corporate infrastructure is researched, particularly suitable for predicting customer churn in CRM systems. The team has proved the effectiveness of many machine learning approaches, including KNN, DT, RF, ANN, and Hybrid SVM + Naïve Bayes via the collection of customer data from Kaggle and its subsequent preparation for model training. According to the investigation results, the hybrid machine-learning model beats individual models, achieving an impressive accuracy of 95.67%. It is essential to use numerous algorithms to improve predictive maintenance in dynamic SaaS systems, since this highlights the value of doing so. In the future, research should be conducted to expand upon these results, with the goal of investigating the benefits and drawbacks of various algorithms while simultaneously working towards the development of more advancements in predictive maintenance approaches. Furthermore, to properly advance this sector, it will be very important to recognize any exceptions and problems that have not yet been handled.

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