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Health Guard AI: A Cloud Customer Relationship Management (CRM) System's Intelligent Customer Health Monitoring Framework for Early Churn Prediction

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ABSTRACT: Customer churn is one of the most serious threats to a Customer Relationship Management (CRM) system, demanding immediate attention as loss of existing customers directly impacts recurring revenue, customer lifecycle value and ultimately the long-term sustainability of the business. The existing approaches for predicting attrition are largely based on traditional data and depend heavily on manneristic behavior when it comes to functionalization of the customer attributes and cannot be used for most of the automated decision-making problems. This paper proposes Health Guard AI: An Intelligent Customer Health Monitoring Framework for Early Churn prediction in Cloud CRM Systems to overcome these limitations. consumer motion analytics, financial indicators, and engagement-level indicators all paintings collectively in the integrated framework to supply a dynamic purchaser fitness rating that represents the general fitness and retention probability of every consumer. month-to-month normal go back on funding corporations can advantage from XG Boost and Random Wooded region, two device learning algorithms, to predict viable churners primarily based on month-to-month product utilization frequency. those algorithms divide customers into three businesses: wholesome, at-risk, and high risk. This system takes under consideration the settlement period, the wide variety of lively clients, and the frequency of guide tickets. This entire-stack framework uses MySQL for database management, Flask for rest APIs, a prediction engine for device research, and an React frontend. We used characteristic significance evaluation to make the version greater clean and easy to understand. We examine the proposed gadget using fashionable overall performance metrics including don't forget, accuracy, precision, F1-score, region under the curve (AUC), and receiver working characteristic (ROC) curves. The results show that health defend AI can appropriately predict client churn whilst additionally presenting useful information for proactive retention strategies and informed enterprise selections. For cutting-edge Cloud CRM structures, the advised framework presents a realistic, up-to-date, and scalable manner to improve client relationship management and client retention.

KEYWORDS: Cloud Customer Relationship Management (CRM), SaaS, client health tracking, XG Boost, device studying, Explainable artificial intelligence (XAI), and Random wooded region.

I. INTRODUCTION

A vital part of any cutting-edge CRM is the cloud-primarily based definitely solution. Cloud patron relationship manage systems were vital to trendy corporations because of their capacity to control customer contacts, income, marketing, and guide offerings thru software software-as-an-company (SaaS) era. patron retention has turn out to be a critical factor of organizational fulfillment because of the developing adoption of subscription-primarily based definitely business models, which rely on routine sales from long-time period customer ties. however, with growing opposition within the marketplace and converting patron expectancies, patron turnover has turn out to be

more of a danger, because of this it is critical for organizations to pick out customers who might also additionally go away early on. [6][7].

Patron churn takes region while customers stop the use of a corporation's offerings terminate their subscriptions. a corporation's bottom line, patron lifetime charge (CLV), and monthly routine sales (MRR) are all hit difficult by means of the use of immoderate churn prices. Cloud patron relationship manage systems constantly produce massive volumes of customer facts, which includes product usage, subscription facts, patron involvement, guide requests, and financial transactions. corporations might also additionally examine hundreds approximately patron behavior and maybe even foresee customer loss by means of the use of studying this fact with AI and ML [6][7].

Facts and historical patron facts are the backbone of conventional churn prediction technique, however they aren't constantly as a good deal as snuff as regards to catching rapid adjustments in behavior and presenting appropriate interpretability. current models often characteristic as opaque structures, rendering churn estimates opaque to patron delight managers, even though advanced gadget learning algorithms like XG Boost and Random wooded area have extensively improved prediction accuracy. in addition, the majority of present day's answers prioritize accurate forecasts over presenting comprehensible records, non-stop patron health monitoring, and connection with cloud-primarily based patron relationship management structures [1][2][6].

The effects of this examine tell Health Guard AI, a cloud CRM churn prediction tool that makes use of synthetic intelligence to song patron health facts. The counseled method employs a mixture of explainable gadget learning, patron behavioral records, and patron health rating computation to discover clients who are in all likelihood to churn. a dynamic purchaser health rating takes into account a number of essential patron characteristics, consisting of monthly routine sales (MRR), product intake, manual fee fee price ticket frequency, settlement duration, and purchaser hobby. clients are categorized as healthful, at-hazard, or slight-hazard using the XG Boost and Random wooded area algorithms, depending on their probability of leaving [3][4][9].

A rest API framework referred to as Flask, gadget learning prediction engine, a MySQL database, and an React-based frontend make up the counseled answer. groups targeted on patron delight can use records to manual retention decisions via utilizing an interactive dashboard that displays real-time data on patron health, churn risk, and issue significance. so that it will obtain this aim, the framework is classed using well-known measures within the industry, consisting of Accuracy, Precision, F1-rating, ROC Curve, AUC, and Confusion Matrix. Health Guard's AI generation offers a scalable, comprehensible, and realistic answer for smart patron retention in modern Cloud CRM structures.

II. PROPOSED SOLUTION

The restrictions of existing customer churn prediction answers are addressed in this observe through providing Health Guard AI, a shrewd framework for tracking customer fitness and early churn prediction in Cloud CRM systems. through integrating monetary indicators, engagement measurements, and customer behavioral information, the technique computes a dynamic customer fitness rating for every patron. the usage of device studying techniques, mainly XG Boost and Randomforest, we are able to continually expect the danger of customer attrition and classify them into three companies: wholesome, At-danger, and high-danger. the usage of a MySQL database, Flask rest APIs, and an React-based frontend, the system provides a scalable full-stack solution for actual-time patron tracking. moreover, function importance analysis enhances version transparency through identifying the important aspects impacting churn estimates. using an interactive dashboard, customer achievement groups are able to see patron fitness, monitor churn danger, and put into effect speedy retention techniques. In sum, the proposed paradigm provides a clean, concise, and realistic manner through which contemporary Cloud CRM environments may additionally improve patron retention and employer selection-making [6]–[11].

III. PROBLEM STATEMENT

Contemporary businesses cannot characteristic without cloud-primarily based CRM systems, which enable them to address client interactions, sales, and support services using software-as-a-service (SaaS) systems. however growing marketplace contention and converting client expectations have led to a huge growth in client attrition. Profitability, consumer lifetime cost (CLV),

and monthly recurring revenue (MRR) have all taken a nosedive due to this. the majority of existing churn prediction answers use historic consumer facts and conventional gadget studying algorithms, neither of which can be continually updated and hence fail to capture the ever-converting nature of client interaction. furthermore, many existing methodologies are black-container fashions with little interpretability; this makes it difficult for consumer achievement teams to understand the reasoning behind attrition predictions. most existing systems also fail to provide real-time analytics, clean integration with cloud CRM systems, and continuous monitoring of consumer fitness, all of which considerably lessen their actual software. a wise and comprehensible framework for tracking client fitness is vital to strengthen proactive retention strategies and enhance lengthy-term CRM. correctly predicting consumer turnover, regularly assessing consumer engagement, and supplying actionable insights are all dreams of this technique [1]–[11].

IV. LITERATURE SURVEY

For a few the churn prediction appears to have captured the interest of CRM and SaaS college students. The essential motive behind this is the unfair monetary state of affairs; attracting a new brand subscriber is a long way more costly than preserving an existing one. This disparity gives entire justification for the advent of styles that could stumble on caution alerts at an early level. in the ultimate ten years, the sphere has been entirely converted via no longer the hassle itself but via the to be had approach for addressing this equipment encompass more lower priced computing, more particular behavioral logs, and an expanding arsenal of AI tactics [6]–[11].

For the maximum part, traditional supervised learning became the place to begin. putting in nicely-set up algorithms inclusive of pressure choice timber, help vector machines, Naïve Bayes, and logistic regression does no longer require a whole lot of infrastructure. customer behavior isn't always linear, and fashions that expect this typically come across a ceiling a whole lot lower than what is achievable on real CRM datasets, which will become more apparent as the information get more complex. The variant became in the main explained the usage of ensemble techniques. a few algorithms that average or improve over a few of weak freshmen are Random Wooded area, Gradient Boosting, Light GBM, and XG Boost. Those algorithms are categorized as choice-certain-unfastened [6][9].

As end result, the excessive-dimensional, chaotic characteristic units generated via CRM systems are better handled, and the possibilities of overfitting are reduced. while XG Boost is renowned for its velocity, regularization, and tolerance for lacking information (that is more enormous than it seems while 1/2 of your CRM fields are blank), Random Wooded area is more renowned for its stability than its performance by myself. maximum contrast studies shown that ensembles outperform unmarried-model baselines in relation to churn responsibilities.

One of the predominant motives why deep learning did not seem until a whole lot later is that, not like ANNs, LSTMs, and transformer architectures, tree ensembles aren't built to take advantage of the sequential nature of client behavior. however, a massive worth may be worth considering. The fashions' actual-international popularity has fallen behind their importance in the observe because of the truth that they require enormous numbers of information and computing fees, which maximum mid-sized SaaS businesses do no longer really have handy. In evaluation to the "are watching for sure/no" approach, any other division of the corporation uses a non-stop customer health score that offers a more entire picture of the chance profile than a final verdict via considering product utilization, MRR, subscription tenure, interest degrees, and assist-rate ticket history. The customer achievement crew can put the previous into practice, in view that it's far more sensible than philosophical to have a prioritized list of money owed which are at chance in place of a binary churn indication given after the truth [1] [2][6]–[8].

Ultimately, once a model is stay, explainability has the capability to be the maximum critical element for businesses. no person desires to decrease fees just because a black box stated so, without an explanation, it's hard to place a cause behind a prediction. the same old techniques for dealing with this hassle have been SHAP, which monitor which abilities truly produced a forecast. This permits stakeholders without technical information to have confidence in the outcome and construct a retention approach round it.

But maximum of this literature doesn't cowl the remaining mile. ideal accuracy and benchmarking articles hardly ever cope with dashboards, cloud deployment, actual-time scoring, and interaction with an actual CRM. Even fewer proposed structures make an effort to finish the full pipeline, which incorporates taking in raw behavioral records, figuring out a health rating, making inferences, developing motives, and offering it in a way that human beings can certainly use it [7][8].

That void is what this attempt is making an attempt to fill an all-inclusive platform for early churn identity inner a Cloud CRM environment is proposed by health protect AI. It integrates health-rating calculation, behavioral analytics, Random wooded area and XG Boost fashions, explainable-AI output, and a React dashboard on top of a Flask backend. a patron success crew's best machine would have a smaller performance hole as compared to a version that does properly on a benchmark [6]–[11].

V. RESEARCH GAP ANALYSIS:

Many gaps within the existing literature on purchaser churn prediction need to be crammed. The maximum massive voids within the existing literature are as follows:

Nearly all patron churn prediction models out now use ancient statistics and focus completely on binary churn type. seeing that these algorithms do not constantly maintain tabs on patron behavior and do not deliver a complete patron health rating, they cannot constantly come across early symptoms of purchaser dissatisfaction.

Predictive precision is more critical than insights that may be explained by means of maximum existing systems. patron success managers have a tough time expertise the number one motives of patron attrition and have much less religion in AI-driven choices seeing that device mastering algorithms like XG Boost and Randomforest regularly feature as black-field models, regardless of their topnotch overall performance.

In want of assessing ML models completely using traditional type metrics, several research push aside practical commercial enterprise requirements. existing procedures hardly ever integrate real-time visualization, patron health tracking, computerized record manufacturing, comfortable person authentication, and a unified framework, which makes them much less applicable to real-world Cloud CRM systems.

There is a loss of complete, reproducible answers in many posted research that simply describe the device mastering model. maximum research do not provide a complete-stack answer that consists of an interactive dashboard, JWT-based totally authentication, a MySQL database, a React-based totally person interface, and record export abilities, for this reason it is tough to apply these ideas to actual SaaS apps.

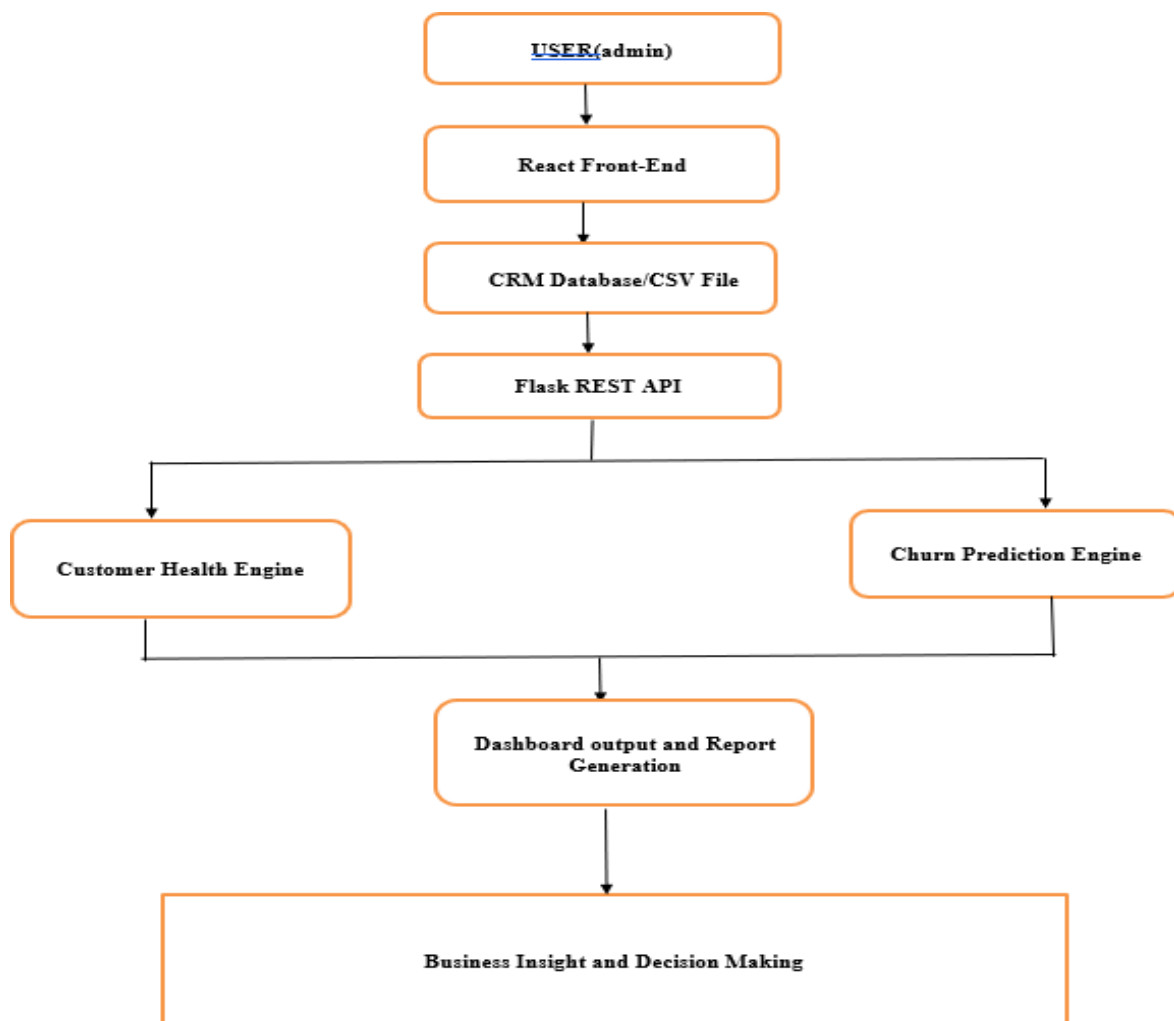
Patron health rating computation, Explainable synthetic Intelligence (XAI), Random forest, and XG Boost algorithms are all part of the proposed health shield AI system, which objectives to provide accurate and obvious churn prediction. The proposed system differs from existing procedures in that it continuously monitors patron behavior, sorts them into healthy, At-threat, and excessive-threat categories, and provides characteristic importance analysis to clarify prediction consequences. additionally, the framework is built as a complete-stack software using React, Flask relaxation APIs, MySQL, JWT-based totally person authentication, an interactive dashboard, and the capability to export reviews to PDF. as it improves prediction accuracy, interpretability, scalability, and practical deployment, this included answer is appropriate for modern-day Cloud CRM systems and proactive patron retention strategies.

There was a lot of look at on predicting patron churn, however there are nevertheless a few critical gaps in our expertise. the bulk of the existing literature handiest looks at patron statistics from the past to categorize binary turnover; it doesn't display patron behavior through the years or compute a complete patron health rating to pick out dangers early on. the lack of interpretability and emphasis on prediction accuracy in many device mastering algorithms makes it difficult for patron success managers to understand the key elements influencing attrition. similarly, existing procedures regularly rely on a handful of patron trends even as ignoring critical behavioral indicators which includes product usage patterns, patron involvement, aid chats, and subscription sports.

VI. MATERIALS AND METHODS

The Health Guard AI software collects patron records without delay from a cloud-based totally CRM to be able to come across early caution signals of patron attrition. The dataset consists of records about subscriptions, contract length, patron profiles, product utilization, monthly

habitual sales, and support ticket records. statistics excellent is improved during preprocessing thru the application of characteristic engineering and normalization following the removal of inconsistent data, duplicates, and missing values. next, we use key economic and behavioral metrics to generate a ever-changing patron fitness score, which we use as a engagement metric. The cleansed statistics is used to educate two churn prediction models: XG Boost and Random woodland. in case you need to get technical, the machine's design is complete-stack, that means it makes use of MySQL, Python, React.js, and Flask relaxation APIs. Java net Token authentication guarantees cozy access. The framework permits customers to export analysis in PDF format and gives a interactive dashboard that displays patron fitness, churn hazard, and prediction findings. This approach integrates explainable statistics, system getting to know, and modern net equipment to provide a scalable retention approach for cloud CRM structures.



6.1 Dataset Description

Patron dating management (CRM) software program as a carrier (SaaS) at the cloud turned into the inspiration for dataset. An extensive spectrum of patron engagement and churn risk is shown in its 1000 patron information. clients' financial, subscription-related, and behavioral information are all part of the information, which is from time to time used to predict when they may leave. each access consists of information approximately the patron, their product utilization, the month-to-month ordinary revenue (MRR), any tickets for assistance, the length of the contract, the final day of hobby, the patron fitness rating, and the actual churn status. The datasets used in our models is summarized in Table 1

Table.1.Dataset description

Attribute	Description
Customer ID	Unique identifier assigned to each customer
Company Name	Name of the customer organization
Usage Drop Percentage	Percentage decrease in product usage compared to previous activity
Support Tickets (30 Days)	Number of support requests raised in the last 30 days
Contract Type (Years)	Customer subscription or contract duration
Monthly Recurring Revenue (MRR)	Monthly revenue generated from the customer
Last Active Days Ago	Number of days since the customer last used the system
AI Health Score	Calculated customer health score (0–100)
Churn Risk	Customer category (Healthy, At-Risk, High-Risk)
Actual Churned	Target variable indicating whether the customer churned (0 = No, 1 = Yes)



Figure.1. Health Score Distribution

VII. METHODOLOGY

7.1 Data Preprocessing and Feature Engineering

The proposed framework starts off evolved with retrieving purchaser records from the Cloud CRM repository. information such as subscription records, settlement duration, purchaser pastime, month-to-month habitual sales (MRR), product usage records, and help ticket records are all a part of the archive. Preprocessing gets rid of reproduction facts, missing values, inconsistent entries, and improves records nice. express houses are translated the usage of label encoding, while numerical capabilities are normalized to make sure consistent scale. characteristic engineering is a similarly step that improves the system getting to know models'

prediction strength. It extracts applicable traits such as the percentage of usage decline, the level of customer engagement, and pastime traits.

7.2 Customer Health Score Calculation

A dynamic consumer fitness rating (CHS) is calculated to assess the overall degree of engagement and contentment for each consumer. Product utilization, aid price tag frequency, monthly routine revenue (MRR), settlement duration, and client pastime are some of the economic and behavioral criteria that play a role in determining the rating. clients with higher fitness scores are believed to be more invested and less susceptible to leaving, while people with lower scores are more susceptible to doing just that. based totally at the calculated rating, clients are categorised into 3 groups:

Healthy (rating > 70), people with a fitness rating among 31 and 70 are considered at risk. patients with a fitness rating below 30 are considered to be at high risk. This grading machine makes it feasible to song consumer actions in actual time and implement preventative measures to maintain clients.

7.3 Machine Learning-Based Churn Prediction

The converted dataset is applied to teach two supervised ML algorithms, namely Random wooded area and XGBoost. Random wooded area constructs many decision trees with bootstrap sampling after which uses majority voting to aggregate their predictions, which improves category accuracy and decreases overfitting. The XGBoost set of rules employs gradient boosting to increase version performance and reduce prediction errors via the gradual creation of decision trees. using customers' monetary and behavioral data, the two algorithms classify them as both healthful, At-chance, or excessive-chance. by using storing and reusing the skilled fashions, the Flask rest API gives actual-time churn estimates via the dashboard.

7.4 Explainable AI and Customer Health Monitoring

To enhance openness, the proposed approach contains Explainable artificial Intelligence (XAI) thru characteristic significance evaluation. For each forecast, the device identifies the maximum vital signs, consisting of reducing product usage, guide price tag frequency, client inactivity, contract time period, and monthly recurring revenue (MRR), in place of simply predicting client attrition. With these easy-to-understand insights, customer success managers can better understand customer behavior and identify the factors that contribute to churn. This helps them develop effective customer retention strategies. An interactive, React-based dashboard provides a real-time view of each customer's predicted health score and churn risk, enabling managers to take timely actions and improve customer satisfaction.

7.5 Evaluation Metrics

The Area Under the Curve (AUC) gauges the classifier's overall discriminative power, whereas the Receiver Operating Characteristic (ROC) curve assesses the trade-off between the True Positive Rate (TPR) and False Positive Rate (FPR).

$$TPR=TP/(TP+FN) \quad FPR=FP/(FP+TN)$$

While a value of 0.5 denotes random classification, an AUC value of 1.0 denotes outstanding prediction performance. The efficacy of the suggested Health Guard AI framework in early customer churn prediction and customer health monitoring is assessed using Accuracy, Precision, Recall, F1-Score, ROC Curve, AUC, and Confusion Matrix.

VIII. RESULTS AND DISCUSSIONS

Fitness guard is an AI framework that can expect while customers will depart a Cloud CRM gadget with the aid of the usage of the XG Boost and Random forest algorithms. One way to degree how properly a model is doing is with the aid of looking at its accuracy, precision, keep in mind, F1-rating, area below the curve (AUC), and confusion matrix. The technique accurately classifies customers as either wholesome, At-threat, or excessive-threat according to their patron fitness rating. reliable prediction overall performance and proactive customer retention are each tested with the aid of the effects of the rather developed patron fitness monitoring gadget.

Table.2.Performance Evaluation of the Proposed HealthGuard AI Framework

METRICS	VALUE
ACCURACY	82.9%
PRECISION	81%
RECALL	88.1%
F1-SCORE	84.4%
ROC-AUC	90.6%
CONFUSION MATRIX	TP=111, FP=26, FN=15, TN=88

The proposed health protect AI framework changed into evaluated the use of ROC-AUC, F1-rating, Accuracy, Precision, and recollect. As visible within the desk, the framework changed into able to appropriately classify the general public of times, with an accuracy charge of eighty 2.9%. With an accuracy rating of 81%, the algorithm is sort of spot-on 4 times out of 5 while predicting an potentially risky scenario. The 88.1% recollect shows that the device correctly identifies maximum real high-chance situations. that is of the maximum importance in a health-chance context, because the results of lacking an real positive bring about some distance worse results than those of an false alarm. The model's F1-rating of 84.4% demonstrates a very good stability among recollect and precision, indicating that neither is being sacrificed for the alternative. The ROC-AUC rating of 90.6% shows that the framework can effectively distinguish among high-chance and occasional-chance situations across a couple of type standards.

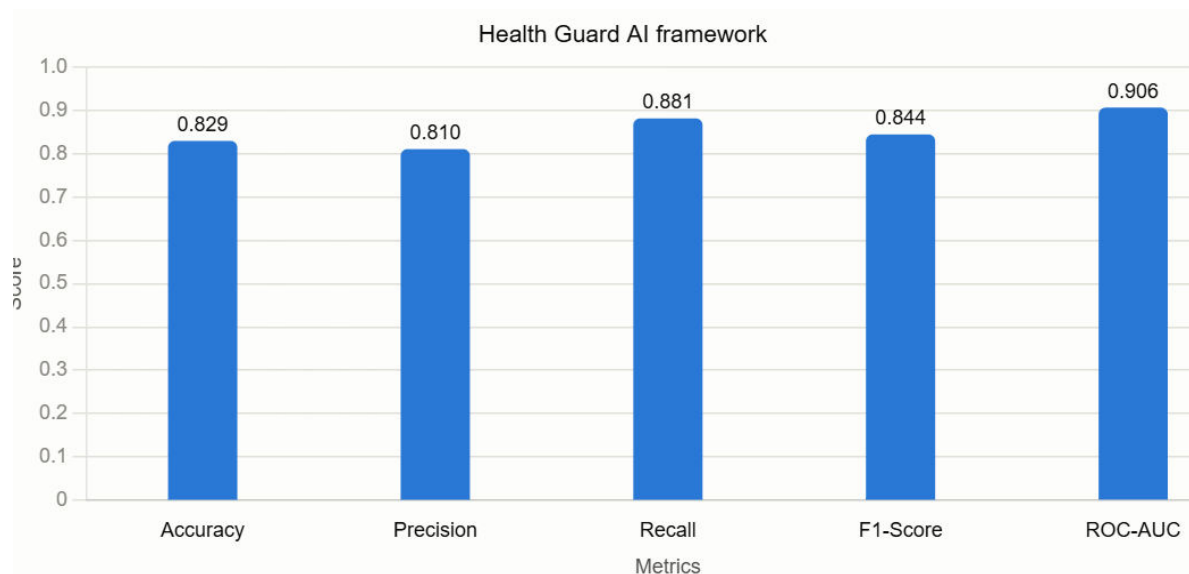


Figure.3. Summary of accuracy, precision,recall, f1-score, ROC-AUC

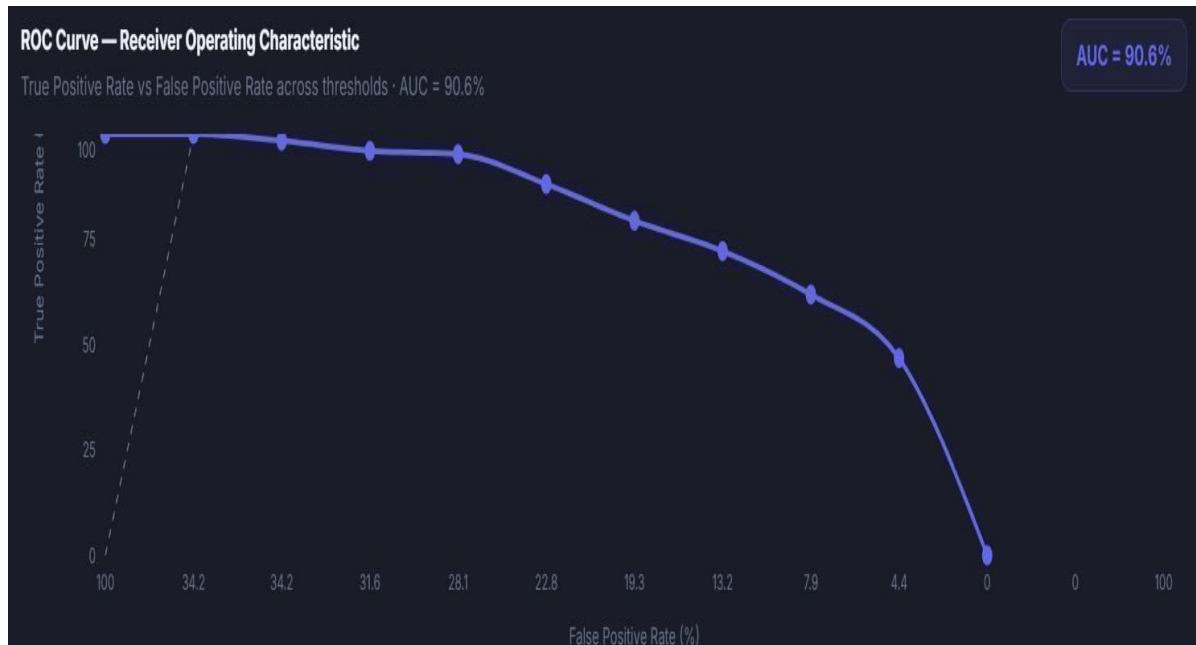


Figure4. ROC Curve for the Proposed HealthGuard AI Framework

Tracing the proper superb rate towards the fake superb rate over specific category thresholds, the ROC curve suggests how efficiently the version differentiates between low-risk and high-risk eventualities. The version acknowledges maximum proper positives while keeping low fake positives in the course of a wide range of constraints, as proven by means of the sharply rising curve that stays within the higher-left corner. At 50% AUC, the version's curve is considerably higher than the dashed diagonal line, which stands for random guessing. The vicinity under the curve (AUC) for this separation is 90.60%, because of this that there's a 90.60% chance that the version will rank a randomly picked high-risk case higher than a randomly selected low-risk case. this is perfect for use as a screening tool while exactly determining risk degrees is paramount, thanks to its high discriminative overall performance.

IX. CONCLUSION AND FUTURE WORK

Health shield AI, supplied in this text, is a Random wooded area—primarily based framework that could discover excessive-hazard scenarios in patient or consumer health facts using go away-one-out cross-validation on 1000 samples. We failed to simply describe the architecture; we additionally skilled and evaluated the device on its own dataset and showed the effects: a classifier with an outstanding 88.10% do not forget and a place below the curve of 90.60%. This finding confirms that the framework can reliably perceive excessive-hazard times with a honest stage of accuracy (81.00%). This balance is a strong point for screening contexts in which the price of missing a real chance case is higher than the price of a false alarm, even though the alternative 210 false positives and 130 false negatives show precise regions that have to be improved. (iv) check out explainable-AI strategies to make hazard predictions more transparent for both end users and physicians.

REFERENCES

- 1) L. Breiman, "Random Forests," Machine Learning, vol. 45, no. 1, pp. 5–32, 2001.
- 2) T. Chen and C. Guestrin, "XGBoost: A Scalable Tree Boosting System," in Proc. 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, San Francisco, CA, USA, 2016, pp. 785–794.
- 3) S. M. Lundberg and S.-I. Lee, "A Unified Approach to Interpreting Model Predictions," in Advances in Neural Information Processing Systems (NeurIPS), vol. 30, 2017.
- 4) M. T. Ribeiro, S. Singh, and C. Guestrin, "'Why Should I Trust you?': Explaining the Predictions of Any Classifier," in Proc. 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, 2016, pp. 1135–1144.

- 5) F. Pedregosa et al., "Scikit-learn: Machine Learning in Python," Journal of Machine Learning Research, vol. 12, pp. 2825–2830, 2011.
- 6) A. Manzoor, M. A. Qureshi, E. Kidney, and L. Longo, "A Review on Machine Learning Methods for Customer Churn Prediction and Recommendations for Business Practitioners," IEEE Access, vol. 12, pp. 70434–70463, 2024, doi: 10.1109/ACCESS.2024.3402092.
- 7) U. G. Joy, K. E. Hoque, M. N. Uddin, L. Chowdhury, and S.-B. Park, "A Big Data-Driven Hybrid Model for Enhancing Streaming Service Customer Retention Through Churn Prediction Integrated with Explainable AI," IEEE Access, vol. 12, pp. 69130–69150, 2024, doi: 10.1109/ACCESS.2024.3401247.
- 8) B. Amiri and S. H. Hosseini, "Unveiling the Power of Social Influence: A Machine Learning Framework for Churn Prediction with Network Analysis," IEEE Access, vol. 12, pp. 71271–71285, 2024, doi: 10.1109/ACCESS.2024.3402684.
- 10) J. Maan and H. Maan, "Customer Churn Prediction Model Using Explainable Machine Learning," arXiv preprint arXiv:2303.00960, 2023.
- 11) S. Bhattacharjee, U. Thukral, and N. Patil, "Early Churn Prediction from Large Scale User-Product Interaction Time Series," arXiv preprint arXiv:2309.14390, 2023.
- 12) D. H. Rudd, H. Huo, and G. Xu, "Causal Analysis of Customer Churn Using Deep Learning," arXiv preprint arXiv:2304.10604, 2023.



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