International Journal of Emerging Research in Engineering and Technology
Pearl Blue Research Group | Volume 7 Issue 1 PP 86-92, 2026
ISSN: 3050-922X | https://doi.org/10.63282/3050-922X.IJERET-V7I1P113

Original Article

Explainable Agentic AI-Driven Machine Learning Framework for Property and General Insurance Risk Assessment

Subhojit Ghosh[1], Srinivas Dadi[2]
[1,2]Independent Researcher, USA.

Received On: 17/12/2025 ***Revised On: 18/01/2026*** ***Accepted On: 28/01/2026*** ***Published On: 03/02/2026***

Abstract *- An accurate premium estimate is not only a fundamental part of effective property insurance but also a guarantee of financial stability for the insurers and reasonable pricing for the policyholders. In this paper, an Explainable Agentic AI-driven framework has been presented, which combines ensemble machine learning with explainability to enhance risk modeling. Exploratory data analysis was done to investigate the distributions of claims, correlations of features, and policy status, and then experiments were done on a high-performance computing environment. Several models were considered such as Logistic Regression, Decision Tree, Random Forest, Gradient Boosting. The findings show that ensemble techniques gave the best performance with Gradient Boosting giving the highest accuracy of 96.10, precision of 96.22 and a recall of 96.10, closely followed by Random Forest with 95.98, yet the performance of Decision Tree and Logistic Regression was moderate. Compared to base models, SVM (Support Vector Machine), DNN (Deep Neural Network), XGB (Extreme Gradient Boosting) and KNN (K-Nearest Neighbors) performed worse. The feature importance analysis showed that the behavioral and demographic variables were some of the strongest predictors, which provided the transparency of the model decisions and met the regulatory needs. The presented results identify the efficacy of ensemble methods in the provision of high predictive accuracy, as well as improved interpretability to provide a more robust and reliable insurance environment.*

Keywords *- Property Insurance, General Insurance, Risk Assessment, Claim Prediction, Insurance Analytics, Explainable Artificial Intelligence (XAI).*

1. Introduction

Insurance is a mechanism that forms the basis of uncertainty management by providing financial safety that allows individuals and businesses to absorb unforeseen losses [1]. With the increase in the size of economies and the growing uncertainty in the environmental state, the necessity of effective and consistent systems of risk mitigation has become more obvious. The dependence on insurance services clearly shows the importance of good evaluation tools, which are able to assist the increasing complication of today's risk situation through securing various physical assets, business transactions and daily life activities against a wide range of possible risks [2]. As urbanization and increased investment in infrastructure continue to unfold, the demand for and variety of insured properties is increasing, thus necessitating the development of more and more robust insurance mechanisms [3]. This growth also increases the frequency of claims, which can result in damage to property, theft, natural disasters, and unintentional losses [4]. The risk patterns of each claim, posted through the claims, show an extra novelty of risk, thus turning the claims process into one of the most important sources of information for understanding the new risk. The complicacy of claim events is growing at the same time and the problems of insurers in realizing the true risks and determining their financial impact are getting harder and harder [5].

The problems mentioned highlight the risk assessment as a major factor which is dealing with the analysis of applicants' profiles, property nature, past activities and area of location in order to find out the probability and magnitude of possible losses [6]. However, traditional risk-assessment methods usually rely on manual analysis and assume parametric statistics, leading to their inability to recognize the dynamic trends and the non-obvious correlations that are typical in large-scale and real-time data [7]. AI and ML have turned into powerful tools that can model complex relationships, detect anomalies, and predict claim outcomes with higher accuracy, among others, to overcome these limitations [8]. However, the opaque quality of most ML models also brings about the issue of trust, transparency and regulatory compliance, particularly in an industry where decision-making process ought to be explainable. To solve this problem, the current paper suggests an Explainable Agentic AI-driven framework of Machine Learning to evaluate the risk in property and general insurance. The framework will provide accurate, transparent, and interpretable risk forecasts through a combination of autonomous agentic reasoning with explainable ML strategies and, therefore, help advance decision-making and a more resilient insurance ecosystem.

1.1. Motivation and Key Contributions

The increasing complexity of the insurance claims is explained by the urbanization, property growth, and the uncertainty in the environment are the demands of the advanced tools of risk-assessment. Conventional approaches based on manual analysis and fixed assumptions are not in a position to document dynamic patterns in big datasets. Machine learning provides better prediction, but it is not as transparent, which is a source of concern in terms of trust and compliance. This inspires the design of an Explainable AI-driven framework to integrate autonomous reasoning with explainable ML to generate high-quality, clear, and resilient risk predictions for the insurance industry. The key contributions are:

- Designed a robust preprocessing pipeline with missing value handling, outlier capping, and feature scaling.
- Applied feature engineering and categorical encoding, and balanced data using SMOTE for fairness.
- Enhanced explainability by analyzing feature importance from the best-performing model, ensuring transparency in insurance risk assessment.
- Validated the framework on a real-world insurance dataset for accuracy and transparency.

The rationale of this study is the increasing complexity of urbanization, expansion of infrastructure, and uncertainty in the environment that expose the weakness of the conventional risk-assessment tools based on manual analysis and fixed statistical assumptions. The difference is a framework of an Explainable AI-driven framework that combines ensemble learning and autonomous thought to attain predictive accuracy and interpretability. Compared with ML models, the proposed framework is more focused on transparency through feature importance analysis, thereby ensuring regulatory compliance and confidence in the decisions made. This paper provides a strong and interpretable insurance risk model by combining useful pre-processing, balancing of classes, and experimentation CPU-based, which contributes to the advancement of reliable AI on financial risk diagnosis.

1.2. Organization of the Paper

The study is organized as follows: Section II reviews related publications, Section III describes the recommended approach, Section IV shows experimental results, and Section V discusses major findings and future research objectives.

2. Literature Review

This section focused on the new developments in property insurance premium calculation, adopting ML techniques. The studies reviewed include:

Polam et al. (2025) presents a machine learning method that uses the XGBoost model to make accurate predictions of property insurance premiums. The XGBoost model proved to be the best performer in prediction with an RMSE of 52.99, MSE of 28.07, and MAE of 30.64 calculated as the mean absolute error. These findings suggest that the model has excellent skills in capturing difficult relationships and providing highly accurate premiums [9].

Brati and Braimllari (2025) employ data gathered from an Albanian private insurance company's vehicle liability portfolio claiming bodily injury from 2018 to 2024, based on 802 instances. Among the evaluation metrics to measure and compare the models' performance were classification accuracy (CA), AUC, confusion matrix and error rates. The XGBoost model was found to have the second-best performance after RF, which had the best classification accuracy (CA = 0.8867, AUC = 0.9437) with the least number of errors. On the other hand, LR demonstrated the poorest results [10].

Kurniawati and Choiruddin (2024) paper proposes a machine learning-based approach that utilizes marketing strategies and the characteristics of insured items in order to predict the trends of claims. The issue of data imbalance is also handled by the authors through application of SMOTE technique. The results indicate that RF outperforms LR with a recall of 96%. The findings assist the insurance companies in a more accurate risk profile assessment and claims volume management [11].

Saikia et al. (2024) emphasize the crucial function of ML in changing the insurance scenery. The ability of accurate forecasts helps insurance companies to use their resources wisely, speed up the processes, and, in the end, improve the quality of service for the customers. The research is mainly concentrated on increasing the efficiency of claim processing. In terms of accuracy, they found the XG Boost performs the best classifier with an accuracy of 0.84 [12].

Yang, Liang and Qi (2023) suggested a useful, non-intrusive technique for assessing the danger of cybersecurity vulnerabilities. Their model employs an ensemble ML approach to evaluate an organization's cyber vulnerability risk using only open source intelligence and publicly available network information data, achieving a precision of 75.6% in comparison to a rating based on comprehensive information by cybersecurity experts [13].

2.1. Research Gap

Despite the effectiveness of ML models in premium prediction and claim classification, as proven by the previous studies, the emphasis is on accuracy and does not address the necessity of transparency, interpretability, and adaptive decision-making. The majority of the works are based on classical supervised models that do not incorporate interpretable or agentic AI abilities and usually focus on particular datasets or types of claims, which do not provide generalizability. These gaps necessitate the necessity of a single, explicatory, and self-sufficient AI-based framework to complete property and general insurance risk evaluation.

3. Methodology

The methodology entails preparation of the dataset through cleaning (high-Missing columns), capping outliers, coding of categorical variables, and data balancing. Normalization of the data is done with StandardScaler and the data is divided into training and testing with 80:20 ratio. Various models LR, DT, RF and GB are trained and tested with the best one described using the feature importance to create accuracy and accountability in insurance risks. Fig. 1 shows the implementation pipeline.

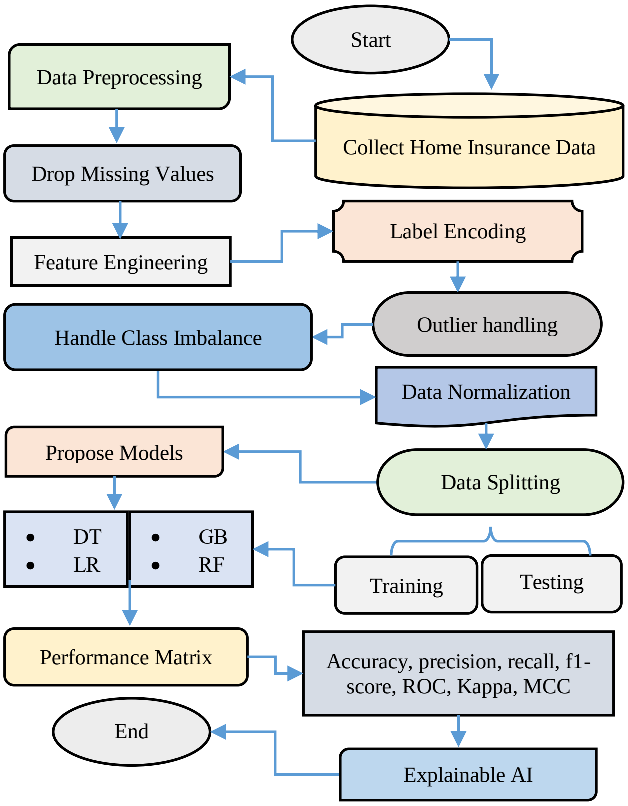

Fig 1: Flowchart for Property Insurance Risk Assessment

All these steps of the flowchart/implementation are explored in next section.

3.1. Data Collection

The Home Insurance dataset of Kaggle is a large set of customer policy records utilized in the assessment of risks in property and general insurance, with approximately 58,000 rows, and 59 features after cleaning, that comprises customer demographics, property attributes, coverage of insurance, indicators of risk, and monetary data, and the objective variable is CLAIM 3 YEARS.

3.2. Data Pre-Processing

There is a high frequency of missing and noisy data in the raw instances. Thus, in order to get useful results, preprocessing primary data is essential. This study uses various pre-processing step that listed in below:

- Drop Missing Columns: Drop columns with more than 50% missing data, then remove any remaining rows with missing values to retain only complete records.

3.3. Feature Engineering and Label Encoding

The feature engineering of the Home Insurance data was to make the raw attributes consumable to model using by transforming QUOTE_DATE and COVER_START into appropriate datetime format, transforming the target variable CLAIM3YEARS into numerical values (1/0) by converting the categorical values (Y/N) into the labelled values, and finally, ensuring that all other categorical values were represented uniformly in numeric format to allow analysis through machine learning.

3.4. Outlier Treatment

Interquartile Range (IQR) was employed as the outlier treatment method in the dataset, which identified and contained the extreme values that were considered as outliers in the data set, instead of dropping them; in this way the data set size would not change and model the data would not be distorted by the presence of extreme values.

3.5. SMOTE for Data Balancing

At first, the dataset was lopsided since the dominant class was much bigger than the minority class. To overcome this problem, SMOTE was applied; the number of classes was placed at par, 21,690 samples. Fig. 2 shows equal distribution reduces model bias and enhances the classifier's ability to learn patterns in minority classes.

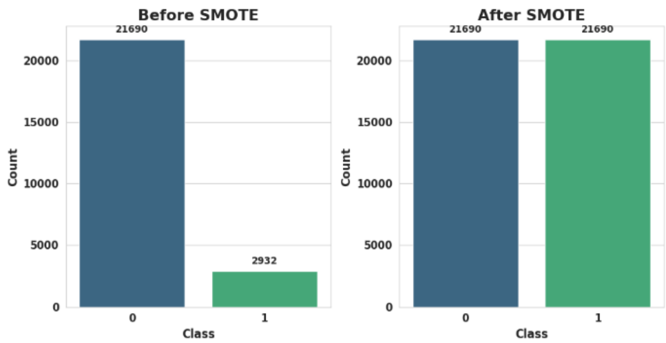

Fig 2: Bar Graph for Original and Balance Class Distribution

3.6. Feature Scaling using StandardScaler

A standardized distribution with zero mean and unit variance is achieved by subtracting the attribute's standard deviation from each value and dividing the result by the standard deviation of the attribute. This process is carried out using the Standard Scaler approach, which employs the Z-score normalization.

$$x_i' = \frac{x_i - \bar{x}}{s} \quad (1)$$

Let x_i be the mean of the x variable, a value x_i is transformed (scaled) into x_i' by means of Equation (1).

3.7. Agentic AI Model Training

The most promising predictions were suggested by this study's exploration of several classifiers. This study makes use of the following classifier algorithms:

- Logistic Regression (LR): The LR method is one of the options for classifying a collection of discrete variables. The logistic regression (LR) is grounded on the logistic sigmoid [14]. This procedure predicts a test item that can be represented to discrete types of two or more will have a certain probability value, by converting the absolute values into numbers ranging from 0 to 1.
- Decision Tree (DT): A commonly used ML algorithm is the decision tree classifier [15]. The model is constructed by successively splitting the data into smaller parts on the basis of the features' assignment rules. The outcome is a tree-like structure, where every node symbolizes a feature and every leaf indicates a class label.
- Random Forest (RF): RF is a method of ensemble learning that benefits from a combination of decision trees creating an even better and more precise outcome[16]. RF produces a bunch of decision trees, thus randomizing different statistical characteristics of the training data. The overall prediction is calculated the same way as the one of the trees in the forest, with each tree being trained on a specific portion of the data.
- Gradient Boosting (GB): GB is an ensemble learning technique that uses a number of weak models to get a stronger forecast. The basic idea behind GB is to construct a model, then use it to find mistakes and train another model to fix them. Iteratively improving the predictions of earlier models continues in this manner until a model reaches a certain level of accuracy.

3.8. Performance Matrix

The evaluation metrics, such as acc, prec, rec, f1score, kappa, MCC, and AUROC, were utilized to determine the capability of the classifiers. The formulas to evaluate all these measures are shown in Equations (2)–(6).

$$Accuracy = \frac{\text{TP+TN}}{\text{TP+Fp+TN+FN}} \quad (2)$$

$$Precision = \frac{\text{TP}}{\text{TP+FP}} \quad (3)$$

$$Recall = \frac{\text{TP}}{TP+FN} \quad (4)$$

$$F1 - Score = \frac{2(Precision*Recall)}{\text{Precision+Recall}} \quad (5)$$

$$AUC = \int_0^1 TPR(x)dx \quad (6)$$

The ratio of properly categorized occurrences to all instances is known as accuracy. The percentage of accurate predictions is known as precision. The ratio of properly categorized positive outputs to correctly classified outputs is known as recall. Additionally, the f1 score is used to evaluate the accuracy of the model, taking into account both its recall and precision. AUROC is a measure of performance that uses adjustments to the true positive and false positive rates to get an outcome. The superb model regards this value as the nearest to 1. Kappa coefficient measures concordance in classification exceeding mere chance, while MCC gives a comprehensive quality of prediction from -1 to +1.

3.9. Explaibale AI

The phrase "explainable AI" (XAI) signifies a collection of methods and mechanisms that allow human beings to view and understand the decision-making process of AI models. XAI, as opposed to conventional "black-box" models, reveals the effect of inputs on outputs, most commonly using methods like feature importance, visualization, or rule extraction. This creates trust, accountability, and adherence to regulations in the critical areas of finance, healthcare, and insurance.

4. Results and Discussion

This section is expected to give comprehensive details about the experimental setup, dataset visualization, and model training results. The experiments were conducted on a Lenovo Legion Pro Core i9-13900HX PC running on Windows 10 with a 3.90 GHz processor and having 32 GB of RAM. They also used the NVIDIA GeForce RTX 4070 GPU to speed up processing. Further details are provided as follows:

4.1. Exploratory Data Analysis

The machine learning lifecycle begins with exploratory data analysis (EDA), which aids in understanding and managing the data collection. An evaluation of the variables' types, a correlation heatmap, and a distribution analysis make up EDA in this investigation.

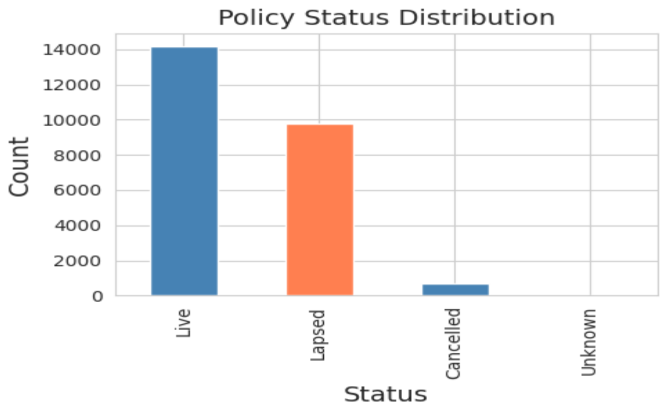

Fig 3: Count Plot of Policy Status Distribution

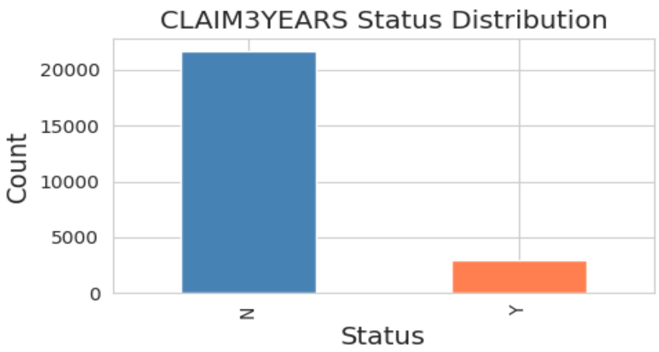

Fig 4: Count Plot of Target feature distribution

Fig. 3 indicates that there are 5,000 claims implying a low claim rate. This distribution shows a good retention of the policies and possible minimal risk exposures to the insurer during the time period in consideration. The frequency of insurance claim within three years; based on status, the frequency was in terms of Y and N as shown in Fig. 4. Most of the policies are under the N category with more than 20, 000 instances meaning that most policyholders never made a claim in this period.

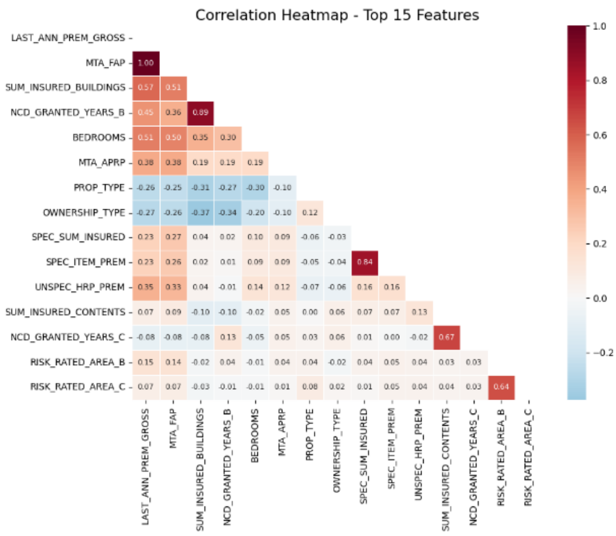

Fig 5: Correlation Heatmap for Top 15 features

The heatmap of correlations shown in Fig. 5 suggests significant relations in the data. The features are strongly positively correlated with each other, and there can be similar effects on the model. Overall, the heatmap helps to realize the redundant features and helps to maximize the features to the model.

4.2. Experiment Results

The results in Table I show that Gradient Boosting (GB) delivers the best performance across all metrics, achieving the highest accuracy, precision, recall, and F1-score, followed closely by RF. DT performs moderately, while LR shows the lowest scores, indicating its limited ability to capture complex risk patterns. The higher MCC and Kappa scores for GB and RF further confirm their superior reliability in property insurance risk assessment.

Table 1: Experiment Results of Proposed Models for Property Insurance Risk Assessment

Performance Metric	GB	RF	DT	LR
Accuracy	96.10	95.98	95.62	94.01
Precision	96.22	96.18	95.74	94.05
Recall	96.10	95.98	95.62	94.01
F1-Score	96.10	95.98	95.61	94.01
MCC Score	92.33	92.16	91.36	88.06
Kappa Score	92.21	91.96	91.23	88.03

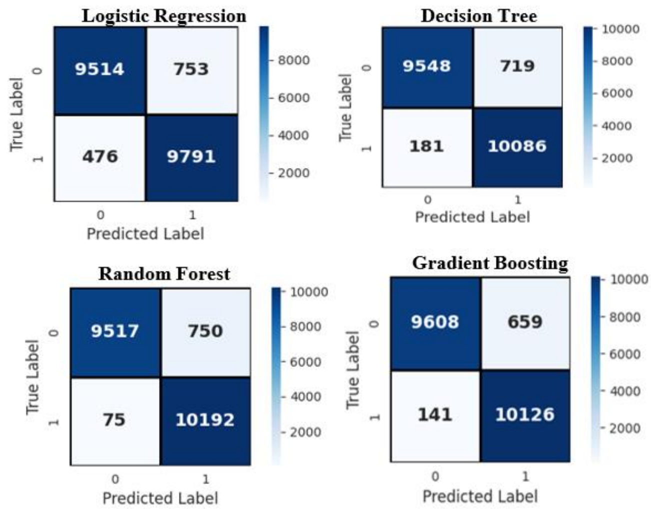

Fig 6: Plot the Confusion Matrix of the all Proposed Models

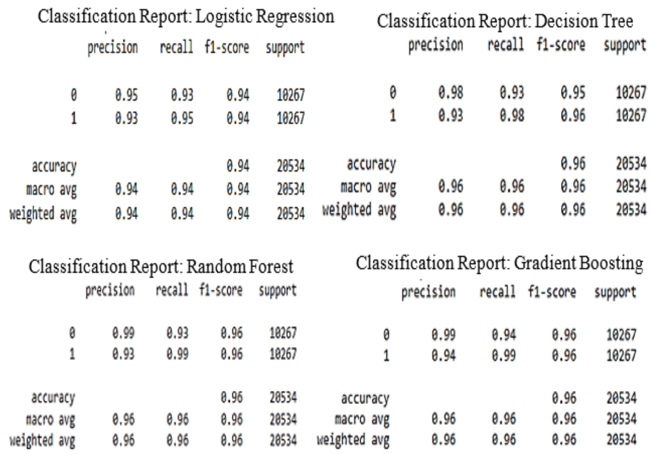

Fig 7: Classification Report of the Proposed Models

Fig. 7 classification report indicates that among the four models (LR, DT, RF, and GB) all are good with a high accuracy (0.94-0.96). Both ensemble techniques, RF and GB are the most robust, with both of 0.96 accuracy and balanced high results on all metrics at both classes, meaning the best and reliable results in this classification task.

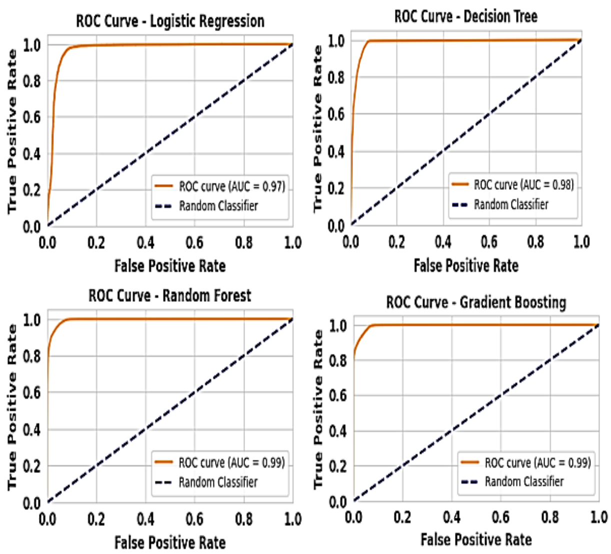

Fig 8: Plot ROC Curve of the Proposed Models

Fig. 8 depicts ROC curves of four models, i.e., LR, DT, RF, and GB, which are employed in phishing detection. With corresponding AUC values of 0.97, 0.98, and 0.99, the findings were all positive and demonstrated the great efficacy of ensemble techniques like RF and GB for a strong cybersecurity defence.

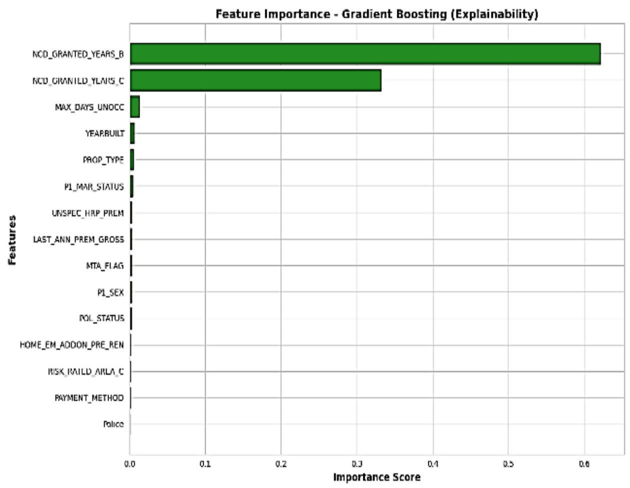

Fig 9: Top 10 most Importance features from the Gradient Boosting Model

Fig. 9 presents the top 10 influential features with NCD_GRANTed_YEARS_D and NCDGRANTed_YEARS C taking the first place. This distribution highlights that this model is based on behavioral and demographic variables to correctly assign risks.

4.3. Comparison and Discussion

Here, the comparison in Table II indicates that ensemble models are the best and that Gradient Boosting (96.10%), Random Forest (95.98%), and Decision Tree (95.62%) models have the highest accuracy and balanced scores, and also Logistic Regression has a good score (94.01%). However, SVM (88.3%), KNN (81.38%), and XGBoost (83.80) performed badly, and DNN was found to be incredibly precise and recalling, but with no accuracy. Altogether, the ensemble methods were the most effective in terms of assessing the risk of property insurance.

Table 2: ML and Dl Models Comparison for Property Insurance Risk Assessment

Model	Accuracy	Precision	Recall	F1-Score
SVM[17]	88.3	82.1	79.8	80.9
DNN[18]	-	93.7	90.1	91.8
XGB[19]	83.80	-	-	-
KNN[20]	81.38	57.81	49.10	53.10
GB	96.10	96.22	96.10	96.10
RF	95.98	96.18	95.98	95.98
DT	95.62	95.74	95.62	95.61
LR	94.01	94.05	94.01	94.01

The study paves a way in advancing property insurance risk assessment by proving the excellence of ensemble learning methods, especially Gradient Boosting and RF, which have a high accuracy and balanced performance in all measures. In addition to predictive power, the model focuses on transparency via feature importance analysis, which guarantees regulatory confidence and understandability of decision-making. The comparative analysis of classical ML and DL models show that ensemble methods are more resistant and reliable to complex risk conditions. Comprehensively, the study will help create a more understandable, scalable, and reliable AI-based insurance system that suits predictive performance to practice industry requirements.

5. Conclusion and Future Study

Due to the rising demand for real estate and the varying amount of claims each month, forecasting property insurance claims has become crucial. The present paper presented an Explainable AI-based Framework of property insurance risk assessment based on powerful preprocessing, balancing of classes and ensemble learning. As shown in experiment results, Gradient Boosting had the best accuracy of 96.10 percent closely followed by Random Forest and Decision Tree at 95.98 and 95.62 percent respectively and Logistic Regression was way behind with the lowest accuracy of 94.01. Comparison to other ML and DL models further proved the best results of ensemble methods: SVM, KNN and XGBoost presented poorer results, whilst DNN presented high precision and recall but did not provide accuracy measurements. Transparency and regulatory compliance was also achieved by the inclusion of feature importance analysis which helps bridge a burning gap of trust and interpretability. On the whole, the explainable AI frameworks make financial risk models more resilient, trustworthy, and data-driven, making such models more robust and contributing to a more robust and reliable insurance ecosystem. Although ensemble models performed well in assessing risks in property insurance, the study has constraints on the use of a single dataset, the limited analysis of deep learning models, and the consideration of structured data only. In the future, datasets shall be increased, multimodal inputs shall be integrated, and hybrid methods shall be considered to improve the accuracy, interpretability, and applicability.

References

[1] Y. Macha and S. K. Pulichikkunnu, “A Data-Driven Framework for Medical Insurance Cost Prediction Using Efficient AI Approaches,” *IJRAR*, vol. 11, no. 4, pp. 887–893, 2024.

[2] V. Verma, “Security Compliance and Risk Management in AI-Driven Financial Transactions,” *Int. J. Eng. Sci. Math.*, vol. 12, no. 7, pp. 1–15, 2023.

[3] R. Jain, “Behavioral Risk Tolerance in U.S. Retirement Planning vs. Property Insurance: A Comparative Analysis,” *Int. J. Appl. Math.*, vol. 38, no. 4s, pp. 41–70, Sep. 2025, doi: 10.12732/ijam.v38i4s.215.

[4] Y. Gao, “Machine Learning in Insurance: Enhancing Pricing, Claim Detection, and Index Insurance Innovation,” in *Proceedings of the 2nd International Conference on Data Analysis and Machine Learning*, 2024, pp. 585–593. doi: 10.5220/0013530000004619.

[5] S. B. Shah, “Evaluating the Effectiveness of Machine Learning in Forecasting Financial Market Trends: A Fintech Perspective,” in *2025 3rd International Conference on Integrated Circuits and Communication Systems (ICICACS)*, 2025, pp. 1–6. doi: 10.1109/ICICACS65178.2025.10968297.

[6] N. Malali, “The Role of Devsecops in Financial AI Models: Integrating Security at Every Stage of AI/ML Model Development in Banking and Insurance,” *Int. J. Eng. Technol. Res. Manag.*, vol. 6, no. 11, 2022, doi: 10.5281/zenodo.15239176.

[7] G. Mantha, “Transforming the Insurance Industry with Salesforce: Enhancing Customer Engagement and Operational Efficiency,” *North Am. J. Eng. Res.*, vol. 5, no. 3, 2024.

[8] S. R. Kurakula, “The Role of AI in Transforming Enterprise Systems Architecture for Financial Services Modernization,” *J. Comput. Sci. Technol. Stud.*, vol. 7, no. 4, pp. 181–186, May 2025, doi: 10.32996/jcsts.2025.7.4.21.

[9] M. Polam *et al.*, “Predictive Modeling for Property Insurance Premium Estimation Using Machine Learning Algorithms,” *Int. J. Recent Innov. Acad. Res.*, vol. 9, no. 3, pp. 55–66, 2025.

[10] E. Brati, A. Braimllari, and A. Gjeçi, “Machine Learning Applications for Predicting High-Cost Claims Using Insurance Data,” *Data*, vol. 10, no. 6, Jun. 2025, doi: 10.3390/data10060090.

[11] R. Kurniawati and A. Choiruddin, “Optimizing Claim Assessment Processes in Property Insurance: A Case Study,” *Procedia Comput. Sci.*, vol. 234, pp. 520–526, 2024, doi: 10.1016/j.procs.2024.03.035.

[12] D. Saikia, R. Barua, M. K. Gourisaria, A. Bandyopadhyay, S. R. Mishra, and S. Bilgaiyan, “Machine Learning Enhancements for Car Insurance Claim Prediction,” in *2024 15th International Conference on Computing Communication and Networking Technologies (ICCCNT)*, 2024, pp. 1–6. doi: 10.1109/ICCCNT61001.2024.10724028.

[13] J. Yang, L. Liang, and J. Qi, “A Practical Non-Intrusive Cyber Security Vulnerability Assessment Method for Cyber-Insurance,” in *2023 8th International Conference on Data Science in Cyberspace (DSC)*, IEEE, Aug. 2023, pp. 261–269. doi: 10.1109/DSC59305.2023.00045.

[14] R. Dattangire, R. Vaidya, D. Biradar, and A. Joon, “Exploring the Tangible Impact of Artificial Intelligence and Machine Learning: Bridging the Gap between Hype and Reality,” in *2024 1st International Conference on Advanced Computing and Emerging Technologies (ACET)*, IEEE, Aug. 2024, pp. 1–6. doi: 10.1109/ACET61898.2024.10730334.

[15] N. Prajapati, “The Role of Machine Learning in Big Data Analytics: Tools, Techniques, and Applications,” *ESP J. Eng. Technol. Adv.*, vol. 5, no. 2, pp. 16–22, 2025, doi: 10.56472/25832646/JETA-V5I2P103.

[16] R. Q. Majumder, “Machine Learning for Predictive Analytics: Trends and Future Directions,” *Int. J. Innov. Sci. Res. Technol.*, vol. 10, no. 4, pp. 3557–3564, May 2025, doi: 10.38124/ijisrt/25apr1899.

[17] C. M. Gangani, “Artificial Intelligence in Insurance : Leveraging Machine Learning for Fraud Detection and Risk Evaluation,” *Intell. Syst. Appl. Eng.*, vol. 12, no. 3, pp. 4503–4514, 2024.

[18] S. R. Adavelli, “Beyond the Claims : Emerging AI Models and Predictive Analytics in Property & Casualty Insurance Risk Assessment,” *Int. J. Sci. Res.*, vol. 13, no. 7, pp. 1625–1631, 2024.

[19] M. A. Omondi, “Interpretable Property Insurance Premium Prediction Using,” *J. Artif. Intell. Auton. Intell.*, vol. 2, no. 2, pp. 349–370, 2025.

[20] N. K. Yego, J. Kasozi, and J. Nkurunziza, “A Comparative Analysis of Machine Learning Models for the Prediction of Insurance Uptake in Kenya,” *Data*, vol. 6, no. 11, 2021, doi: 10.3390/data6110116.