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Artificial Intelligence in Life Insurance Underwriting: A Risk Assessment and Ethical Implications

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Abstract: *The underwriting of Machine learning (ML) and artificial intelligence (AI) are transforming life insurance, which enables quicker, more precise, and data-driven risk assessment procedures. In order to assess and contrast this study uses a real-life insurance dataset to examine the efficacy of three predictive modelling techniques: Classifiers such as Random Forest (RF), Stochastic Gradient Descent (SGD), and Neural Networks (NN). The neural network model achieved 100% recall, 98% accuracy, 98% precision, and a 99% F1-score, significantly outperforming the other models. Extensive data preparation methods were used, such as solving class imbalance and enhancing model robustness, outlier identification and removal, and missing value imputation. This technique is called Synthetic Minority Over-Sampling (SMOTE). The study critically analyzes ethical issues, including algorithmic openness, fairness, and data privacy, in addition to model performance, to facilitate the ethical use of artificial intelligence. With the goal of increasing operational effectiveness and promoting equity and trust in life insurance underwriting procedures, the suggested framework emphasizes the significance of both technical excellence and ethical accountability*

Keywords: Artificial Intelligence (AI), Machine Learning (ML), Life Insurance Underwriting, Risk Assessment, Neural Networks (NN), Random Forest (RF).

I. INTRODUCTION

Advances in AI are bringing transformative change to the life insurance industry. Traditionally, the process of underwriting has depended heavily on manual assessments as well as actuarial models, which, by extension, have created many markets to work out of. The use of AI has significant potential however now with an increased volume of digital data and more ML technologies [1], this technology has proven to be a powerful asset to optimize underwriting efficiency, more accurately risk stratify, and improve personalization service to the customer in the form of insurance products [2].

In the United States, AI and ML are reconfiguring the face of the insurance industry in the risk assessment and underwriting [3]. Prior to arriving at the broad realm of AI, traditional underwriting, which relied on both human thought and manual evaluation of historical claims data, had started to be augmented and in many cases [4], completely replaced by algorithmic models which run over massive data sets in real time. Major insurers are using [5] in an industry worth over 1.4 trillion USD. Over the centuries, data analysis has been important to insurance operations [6].

Rigid rule-based systems have long been used by the underwriters to determine premiums and coverage of risk. Customer data is routinely collected in vast quantities by insurers during sales of policies, which is then modified during the claims process [7]. This data becomes important for use in revising risks when clients apply for coverage from different insurers [8]. Therefore, the insurance companies are increasingly recognizing the value of business intelligence tools to minimize the underwriting turnaround time, to improve customer service, to expedite claim processing, and to reduce fraudulent activity [9].

Several key advantages of integrating AI into life insurance underwriting are brought [10]. When it comes to structured and unstructured data at large scales, AI systems are tremendous at-risk predictions and real-time quote generation. Furthermore, it enhances operational efficiency and enables the provision of more personalized policy offerings

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according to individual client profiles [11]. It is additionally remarkable that by automating repetitive underwriting tasks, AI will liberate underwriters from such routine involvement to concentrate on higher-level, SR-oriented requirements for example, portfolio optimization, risk diversification [12]. However, as AI is increasingly integrated into underwriting, many difficult ethical questions arise as to whether the benefits outweigh the problems [13].

Being of concern, among other things, are algorithmic bias, transparency, accountability, and data privacy [14]. Without superintendence, AI models might otherwise entrench discrimination or make opaque, opaque decisions that are un-auditable or in explainable [15]. This paper's goal is to examine critically how AI is making a role in life insurance underwriting both in terms of technological advancements and the ethical issues it raises [16]. This study will review current practices using a comprehensive review of current practices, risk modeling techniques [17], and the regulatory frameworks [19] in the involvement of insurers in the innovation of underwriting systems with fairness and accountability using AI.

A. Motivation and Contributions of the Study

The growing use of data-driven technologies, AI, and ML is causing the life insurance industry to undergo maturation, and in underwriting and risk assessment most especially. Traditional underwriting methods include methods that are very slow, inconsistent, and biased by humans who are relying heavily on manual evaluation and historical claim data. On the side of the adoption of AI, there are also some ethical concerns that should be taken into account, such as algorithmic bias, data privacy risks as well and non-transparency with automated decision-making. The use of ML in life insurance underwriting for motivation has been the main focus of this work, both by the need for better risk modeling and responsibility in ethical terms. The key contributions of this study are:

- Building a complete ML pipeline for the risk assessment for life insurance based on an actual database.
- Preprocessing the data with missing value imputation, outlier removal and class balancing with SMOTE to make data quality and fairness.
- Generating benchmark performance while building a neural network model and contrasting it with RF and SGD classifiers according to F1 score, precision, accuracy, and recall.
- This discussed how AI can help improve underwriting efficiency effectively at the same time as being fair, transparent, and responsible when used in the insurance sector.

B. Novelty of paper

At present, although life insurance underwriting is radically transformed by AI, there are still very few who achieve a proper balance between both technical efficiency and ethical integrity. introduce this work in a new framework of the combination of fairness-aware preprocessing and ML to ensure fair decision-making. Different from other works, this work simultaneously places emphasis on tailoring the existence of accurate risk prediction and the deployment of responsible AI. The research addresses important problems, such as bias in algorithms, transparency, and data governance, and thereby closes a critical service gap in the creation of trustworthy, data-driven underwriting systems for the insurance sector.

C. Structure of the paper

The paper is structured as follows: In the second II, it review related work of AI applications for insurance underwriting and the major ethical concerns. The suggested technique is described in depth in Section III. A discussion follows the comparison of the model's performance with the experimental data in Section IV. The paper's main conclusions are presented in Section V, which also suggests future study topics in ethical and data-driven life insurance underwriting.

II. LITERATURE REVIEW

The literature emphasizes how AI may revolutionize life insurance underwriting by improving risk assessment through insights derived from data. It emphasizes ethical considerations, potential biases, and the necessity of justice and openness in automated decision-making.

Boodhun and Jayabalan (2018) it seeks to enhance life insurance firms' risk assessment through the use of predictive analytics-based tools. An essential part of classifying candidates in Risk assessment is the industry for life insurance.

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The dataset was subjected to ML techniques such as multiple LR, ANN, REPTree, and RT classifiers in order to measure the applicants' risk level. The results demonstrated that in contrast to the other models, the REPTree technique was the best appropriate algorithm for the CFS approach, with the lowest RMSE value of 2.027 and the lowest MAE value of 1.5285. Multiple LR outperformed the PCA, which, with corresponding RMSE and MAE values of 2.0659 and 1.6396, has the lowest [18].

Lai, Wu and Tseng (2021) clarifies the connections between life insurance salespeople's conflicts of interest, moral leadership, moral judgment, and moral instruction. This study aims to investigate how interest conflicts impact the ethical attitude and intention of life insurance salesmen, with a focus on the importance of ethical leadership and ethical training. 757 Questionnaires are given to full-time life insurance salespeople. Tests like partial least squares regression and analysis of variance are used to examine data. The main conclusions demonstrate that the types of conflicts of interest change the moral stance and goals of life insurance salespeople [19].

Islam et al. (2021) order to detect unfavorable behavior (AB), it looks at how the policyholder behaves when they have life insurance. In this paper, a novel association rule learning-based approach called "ARLAS" is presented to ascertain policyholders' AS conduct. 10% of the items in the test set had their attribute values randomly flipped to create a synthetic dataset in addition to the original AS dataset. 31,800 Australian life insurance clients participated in the study, and the findings show that the recommended approach considerably boosts performance as compared [20].

Kgare (2021) demonstrate how ensemble models (RF and GB) are better at making predictions than single classifiers, and there is compelling evidence that model boosting and appropriate parameter changes enhance model performance. GB is the best classifier overall, with 92%, 76%, and 92%, 84% F-measures for the Insurer 1 and Insurer 2 datasets, respectively. Since ensemble models have been shown to be more effective than single-model classifiers in predicting life insurance lapses, the study advises using them instead [21].

Rusdah and Murfi (2020) evaluated how well the XGBoost model predicts risk of life insurance when there is incomplete information. The simulations demonstrate that one of the XGBoost models that has undergone imputation preprocessing has accuracy equivalent to those that have not. The insurance industry uses insurance risk prediction to categorise different risk levels. ML claims that predicting danger levels is a problem with multi-class categorization. The history data of the insurance applicant may have missing values, thus, these issues must be addressed in order to improve performance [22].

Mustika, Murfi and Widyaningsih (2019) help classify assist in rapidly classifying potential insurance applicants according to their degree of risk. XGBoost, a DT-based ML algorithm, is one example with life insurance, this model is used for risk prediction. The XGBoost model's accuracy value is raised by overcoming the missing values in the data using a variety of data processing approaches. The results of the study show that the XGBoost model, which has an accuracy of 0.60730 using kappa units, is very relevant and useful for forecasting the volume of risk claims for life insurance applicants [23].

Table I lists research gaps in AI in Life Insurance Underwriting, highlighting restrictions on regulatory compliance and data openness. While current applications demonstrate efficiency gains and improved risk assessment, challenges remain in addressing ethical concerns, ensuring fairness, and managing data privacy, highlighting the need for more accountable and trustworthy AI systems in underwriting.

Table: Summary of the related work on AI in Life Insurance Underwriting Risks and Ethics

Reference	Focus Area	Methodology	Key Findings	Limitations	Research Opportunities
Boodhun and Jayabalan (2018)[18]	Risk assessment using ML	REPTree, ANN, MLR, Random Tree; CFS and PCA feature selection	REPTree (CFS) showed lowest MAE (1.5285), MLR (PCA) showed lowest RMSE (2.0659)	Limited dataset; focused only on technical accuracy	Expand to deep learning methods and larger, real-world datasets
Lai, Wu and Tseng (2021)[19]	Ethical decision-making in	Survey of 757 salespeople; ANOVA & PLS	Interest conflicts influence ethical attitudes; ethical	Regional sample limits generalizability	Explore cross-cultural ethics in AI-supported

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	sales	regression	training is crucial		underwriting
Islam et al. (2021)[20]	Detecting adverse behavior in policyholders	ARLAS: Association rule learning-based method	High performance in detecting adverse behavior on synthetic data	Synthetic data may not reflect real-world conditions	Validate with real-world data and assess fairness of detection algorithms
Kgare (2021) [21]	Ensemble model effectiveness for lapse prediction	Compared single vs. ensemble models (GBM, RF)	Gradient Boosting achieved up to 92% accuracy	Limited focus on interpretability and ethical concerns	Design interpretable ensemble models with ethical guidelines
Rusdah and Murfi (2020)[22]	Handling missing values in life insurance risk prediction	Evaluated XGBoost with/without imputation	Comparable accuracy even without imputation preprocessing	No detailed fairness or privacy assessment	Explore bias due to missing values and enhance model explain ability
Mustika, Murfi and Widyaningsih (2019)[23]	Classifying applicants based on risk	Used XGBoost with data preprocessing	Achieved 0.6073 accuracy with kappa metric	Moderate accuracy; lacks ethical analysis	Improve model performance and integrate fairness-aware preprocessing

III. METHODOLOGY

A thorough technique for evaluating life insurance risk using ML is presented in Figure 1. It begins with acquiring a life insurance risk assessment dataset, followed by data preparation procedures, such as class balancing using SMOTE, managing missing results, and removing outliers. The data is separated into training and testing sets after being preprocessed. To evaluate performance, a proposed NN model is compared with an RF and SGD classifier. Important performance indicators are used to compare the models, including as precision, accuracy, recall, and F1 score. The outcomes of these indicators ensure accurate and fact-based risk assessment by assisting in the identification of the best model for forecasting life insurance risk. This methodology aims to enhance decision-making in the insurance domain by integrating advanced data-handling techniques with robust ML models.

A. Data Collection

The study's dataset includes of 15,000 anonymized life insurance application records, including demographic (age, gender), health-related (BMI, blood pressure, pre-existing conditions), behavioral (smoking status, physical activity), and policy-specific features (claim history, risk classification). Collected from historical underwriting data, this dataset enables supervised learning for risk assessment and reflects real-world life insurance scenarios. To guarantee a thorough assessment of the generalizability and accuracy of the model

B. Data Preprocessing

A number of preparation techniques were implemented to get the dataset ready for modeling. The SMOTE was employed to create synthetic samples for the under-represented high-risk class, which was necessary due to the class imbalance [24]. Missing numerical values were imputed using column means, while categorical values were handled using model-based imputation. Outliers in features like Age and BMI were detected and eliminated by applying the IQR technique. The IQR method was used, where any value falling below was considered an outlier and removed Equation 1.

$$Outlier\ if\ x < Q1 - 1.5 \times IQR\ or\ x > Q3 + 1.5 \times IQR \qquad (1)$$

Q1 = 25th percentile (lower quartile)

Q3 = 75th percentile (upper quartile)

IQR = Q3 − Q1

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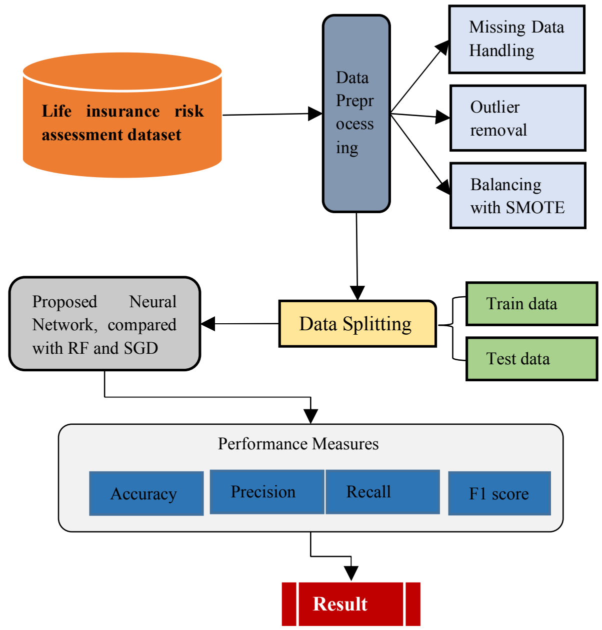

Figure 1: Flowchart of Life Insurance Risk Assessment

A correlation matrix was created to identify and address multicollinearity. Feature engineering included binning continuous variables (e.g., Annual Income, Blood Pressure) and applying one-hot encoding to categorical features (e.g., Occupation Risk, Smoker), ensuring the dataset was optimized for model training.

Figure 2, presents a correlation matrix heatmap illustrating the relationships between life insurance underwriting features. Notable correlations include Age and Family_History (0.72), Exercise_Frequency and Alcohol_Consumption (–0.50), and BMI and Blood_Pressure (0.60). The target variable shows a moderate correlation with Cholesterol (0.42) and Smoker (0.27). These values help identify strongly related features for effective model selection and improved prediction accuracy.

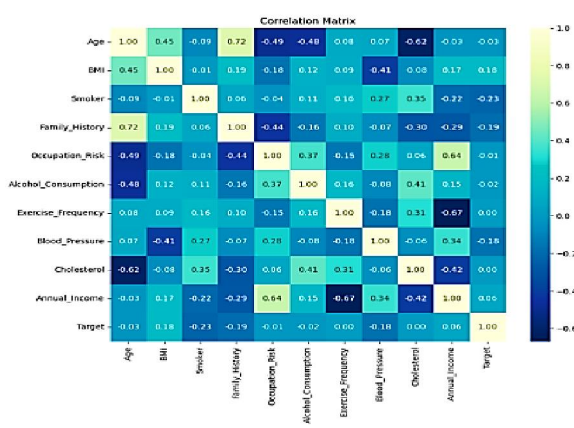

Figure 2: Correlation Matrix of Life Insurance Risk Assessment Features

C. Data Splitting

There are two parts to the dataset: In order to ensure A comprehensive evaluation of the model's accuracy and generalizability predictions in evaluating risk across different policyholders' profiles, the first is utilized for 80% of the training, and the second is for 20% of the testing.

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D. Implementation of Neural Network Model (NN)

Mathematical models known as NN replicate the functioning of the human brain. NN have the extra advantage of being able to simulate almost any non-linear relationship between input and destination variables. Nazari and Alidadi (2013) state that it is becoming more and more significant in financial applications for tasks like time series forecasting, pattern recognition, and classification. It is made up of three primary parts: the output, the concealed layer or levels, and the input data. The MLP is another name for it. The units of an "input" layer are linked to a layer of "hidden" units, which are linked to the units of an "output" layer. Neurons communicate stimuli through connections. When a stimulus is received, the weight associated with each link multiplies itself. Graphics are the greatest way to view this. Each neuron then plays a part in the activation function that determines the output stimuli [25]. A transformation function and weighted summation functions are the two processes that make up the hidden(s) layer of a feedforward/back propagation neural network representation. The input data value and the output measurements are connected by two functions. The technique of normalizing input data between 0 and 1 is known as data normalization. Resilient backpropagation is used to train an MLP neural network in order to identify the best neural network. As activation functions in this study, the hyperbolic tangent and sigmoid function were employed.

The associated weights are $w\boldsymbol{i}$, i = 1,2,3,4,5, and the input signals are Xi, i = 1,2,3,4,5, with a limit of k. Equations 2 and 3 provide this model's degree of activity.

$$\alpha = \sum_{i=1}^{N} W_{ij} X_j \quad (2)$$

In the meanwhile, the output layer's two neurons provide the binary output appears as Equation 3,

$$y = \begin{cases} 1 & , a \geq k \\ 0 & , a < k \end{cases} \quad (3)$$

E. Performance Measures

In life insurance risk assessment, performance measures are critical for evaluating the precision and dependability of forecasting methods. Accuracy (general correctness), precision (correct positive predictions), recall (capacity to recognized TP), Common performance metrics include the F1-score (balance between recall and accuracy), for instance. These measures ensure effective risk stratification, help minimize losses, and support fair and efficient underwriting decisions. The four metrics, TP, TN, FP, and FN, form the foundation of evaluating classification model performance.

- True Positive (TP): The percentage of expected values that turn out to be true and positive.
- True Negative (TN): The percentage of negative expectations that imply that the actual values are also true.
- False Positive (FP): It is sometimes referred to as a Type 1 error. The proportion of first expected positive numbers that turn out to be inaccurate.
- False Negative (FN): Type 2 Error is another name for it. The proportion of expected negative values that turn out to be false.

The following formula is used to calculate precision, accuracy, recall, and F1-score:

Accuracy

The accuracy of a model is determined by calculating how well it can classify data [26]. Additionally, accuracy can show how well predicted and actual values match. Equation 4 is displayed below.

$$Accuracy = \frac{TP+TN}{TP+FN+FP+TN} (4)$$

Precision

One metric for assessing the degree of accuracy between the model's anticipated outcomes and the available data is precision. To ascertain the percentage of genuinely positive data among all the positive data that the algorithm has forecasted, accuracy. In Equation 5, the calculated accuracy is found.

$$P = \frac{TP}{(TP+FP)} \quad (5)$$

Recall

The best model can also be chosen from a variety of tested models using recall (sensitivity). Recall calculates the proportion of genuine positive facts to true positive forecasts. Equation 6 showed the recall value.

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$$R = \frac{TP}{TP+FN} \quad (6)$$

F1-Score

It is possible to assess a model's overall performance using the F1-score, It is a single figure representing the accuracy and recall harmonic mean. Equation 7 computes the F1 score.

$$F1 = 2 \times \frac{Precision \times Recall}{Precision + Recall} \quad (7)$$

To ensure accurate risk assessment, better underwriting choices, and less financial uncertainty, the performance metrics in life insurance risk analyze model efficacy using F1-score, recall, accuracy, and precision.

IV. RESULT ANALYSIS AND DISCUSSION

This study investigates the use of AI to life insurance underwriting, particularly with regard to NN risk assessment models. All of this was done on a Windows 11 machine running Python 3.10 with an Intel® Core i5-1135G7 CPU and 16 GB of RAM using a Jupyter Notebook. As seen from the Table II, the NN model demonstrated 98% accuracy, 98% precision, 100% recall and 99% F1 score, indicating that such model is reliable at identifying underwriting risks with low number of false negatives. A comparison was also made for other models, such as RF and SGD. Nevertheless, the NN model's overall performance was superior. The implications of these findings confirm AI's ability to increase fairness, efficiency, and accuracy in life insurance underwriting.

Table 2: Efficacy of Neural Network Model in Predictive Risk Modeling for Life Insurance

Performance Metrics (%)	**Neural Network**
Accuracy	98
Precision	98
Recall	100
F1-score	99

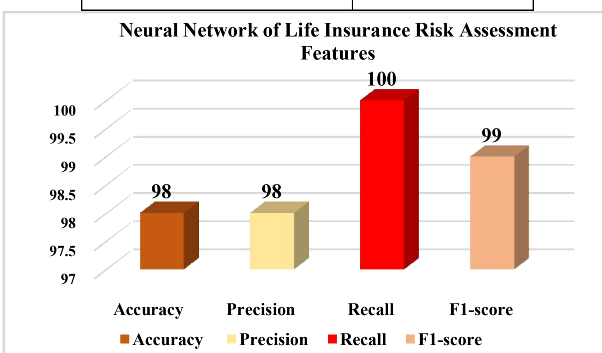

Figure 3: Neural Network Model in Predictive Risk Modeling for Life Insurance

Table II and Figure 3, which show the outcomes of the neural network model in predictive risk modeling for life insurance underwriting, provide examples of this. This model demonstrated overall effectiveness by achieving a 98% accuracy rate in proper classifications. It has a significant ability to accurately detect TP high-risk situations, and its accuracy (98%) is quite good. With a 100% recall, the model was able to accurately forecast every real high-risk person without producing any FN. With a 99% F1-score, it demonstrates that the model is doing well in terms of balanced precision and recall, making it appropriate for accurate and dependable risk assessment in life insurance underwriting.

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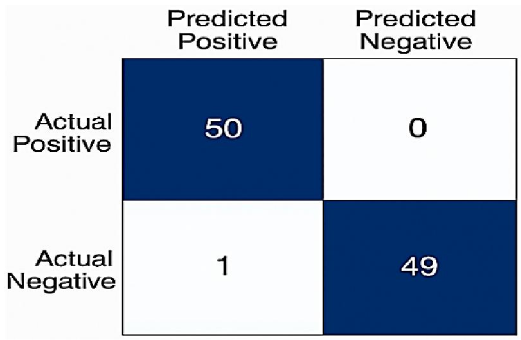

Figure 4: Confusion Matrix of Neural Network Model in Predictive Risk Modeling for Life Insurance

The neural network model's ability to predict life insurance risk is shown in Figure 4. The model correctly classified 50 out of all predictions, positive into positive and negative into negative. It only recorded 1 false positive - where a low-risk individual was falsely marked as high risk and no FN- no high-risk individual was missed.

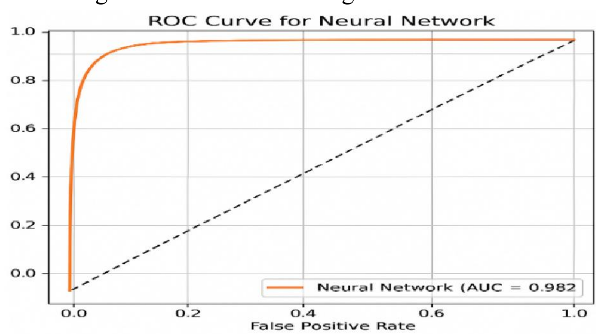

Figure 5: ROC Curve for Neural Network in Life Insurance Risk Classification

Figure 5 illustrates the robustness of the neural network model in predicting life insurance risk. With an AUC of 0.982, the model demonstrates excellent discrimination between high-risk and low-risk applicants. High accuracy and reliability are indicated by a steep curve and a small false positive rate.

A. Comparative Analysis

In this section, this paper discusses the life insurance underwriting problem through a comparative analysis of ML models impacted by AI risk assessment. Table III demonstrates how the NN performed best, achieving 99% F1-score, 100% recall, 98% accuracy, and 98% precision, showing very great performance when distinguishing high-risk applicants and minimizing false negatives, which is very important to prevent loss of claim and fair eligibility decisions. The RF model recorded 82% accuracy, 76% precision, 72% recall, and a 74% F1-score, indicating a performance that is balanced but not as strong as NN. At the same time, SGD demonstrated the weakest performance, achieving 64.7% accuracy, 53.2% precision, 64.2% recall, and 55.1% F1 score, which indicates that Stochastic Gradient Descent cannot fully capture complex patterns in the underwriting data. This implies that neural networks are superior to traditional life insurance risk models. Furthermore, they emphasize the ethical reason for developing such accurate and fair AI systems to eliminate bias, avoid unjust exclusions, and give transparency in underwriting practices.

Table 3: Comparative Study of ML Algorithms for Predictive Risk Modeling for Life Insurance

Models	**Accuracy**	**Precision**	**Recall**	**F1-score**
NN	98	98	100	99
RF[27]	82	76	72	74
SGD[28]	64.7	53.2	64.2	55.1

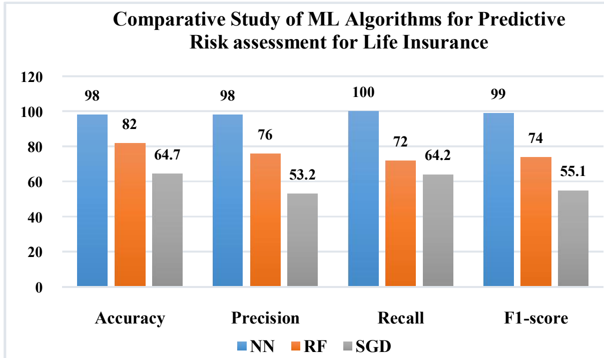

Figure 6: Comparative Study of ML Algorithms for Predictive Risk Assessment in Life Insurance

As shown in Figure 6, NN, RF, and SGD algorithms have been compared for the risk evaluation for life insurance. The NN model has a 99% F1-score, 100% recall, 98% accuracy, and 98% precision in each statistic, the highest performance, which indicates that it performs well in predictive underwriting in comparison to SGD and RF.

V. CONCLUSION AND FUTURE SCOPE

Finally, integrating AI, in particular, NN models in life insurance underwriting can improve the traditional processes in terms of smartness, speed, and data-driven decision making. Through good data preprocessing, model training, and evaluation, AI will be able to identify some of the more intricate and risk factor-oriented patterns that will allow for more accurate and consistent underwriting outcomes. This implies more fair and personalized assessment and streamlines the operation. In order for the industry to continue to advance, explainable AI innovation, the use of dynamic health data, and a steadfast commitment to ethical considerations will be essential to foster a user's trust in and long-term success with the use of AI in underwriting systems.

Future research into AI-based life insurance underwriting needs to create XAI methods that help underwriters understand AI-driven decisions while building trust in those decisions. The accuracy of health risk assessments and the personalization of risk profiles may be enhanced by integrating wearable technology's real-time and dynamic health data into electronic health records. The hybrid systems of DL models with rule-based systems that are the implementation of an organization's high performance and understandable AI assessment results would be beneficial. Three things are needed in the creation of ethical underwriting solutions: data privacy standards together with the prevention of algorithmic biases, and regulatory standards for compliance. Long-term research studies following AI decisions in actual underwriting practices will deliver essential findings that help develop the models throughout their life cycles.

REFERENCES

[1] V. Kolluri, "A Comprehensive Analysis on Explainable and Ethical Machine: Demystifying Advances in Artificial Intelligence," Int. Res. J., vol. 2, no. 7, 2015.

[2] P. Pathak, A. Shrivastava, and S. Gupta, "A survey on various security issues in delay tolerant networks," J Adv Shell Program., vol. 2, no. 2, pp. 12–18, 2015.

[3] Vikas Thakran, "A Review of 3D printing methods for pharmaceutical manufacturing: Technologies and applications," Int. J. Sci. Res. Arch., vol. 4, no. 1, pp. 250–261, Dec. 2021, doi: 10.30574/ijsra.2021.4.1.0207.

[4] K. Murugandi, "End-to-End SAP Implementation in Global Supply Chains : Bridging Functional and Technical Aspects of EDI Integration," Int. J. Res. Anal. Rev., vol. 8, no. 2, pp. 894–900, 2021.

[5] M. Maier, H. Carlotto, S. Saperstein, F. Sanchez, S. Balogun, and S. Merritt, "Improving the accuracy and transparency of underwriting with AI to transform the life insurance industry," Ai Mag., vol. 41, no. 3, pp. 78–93, 2020.

[6] S. S. S. Neeli, "Ensuring Data Quality: A Critical Aspect of Business Intelligence Success," Int. J. Lead. Res. Publ., vol. 2, no. 9, p. 7, 2021.

[7] V. S. Thokala, "Integrating Machine Learning into Web Applications for Personalized Content Delivery using Python," Int. J. Curr. Eng. Technol., vol. 11, no. 06, 2021, doi: https://doi.org/10.14741/ijcet/v.11.6.9.

[8] Y. H. Rajarshi Tarafdar, "Finding Majority for Integer Elements," J. Comput. Sci. Coll., vol. 33, no. 5, pp. 187–191, 2018.
[9] M. Maier, H. Carlotto, F. Sanchez, S. Balogun, and S. Merritt, "Transforming Underwriting in the Life Insurance Industry," Proc. AAAI Conf. Artif. Intell., vol. 33, no. 01, pp. 9373–9380, Jul. 2019, doi: 10.1609/aaai.v33i01.33019373.
[10] G. Modalavalasa, "Towards Sustainable Development Based on Machine Learning Models for Accurate and Efficient Flood Prediction," vol. 8, no. 2, pp. 940–944, 2021.
[11] N. Patel, "Sustainable Smart Cities : Leveraging IoT and Data Analytics for Energy Efficiency and Urban Development," J. Emerg. Technol. Innov. Res., vol. 8, no. 3, 2021.
[12] T. Kolosova and S. Berestizhevsky, "The Anatomy of Artificial Intelligence Solution for Automation of Underwriting Decision-Making Process," pp. 1–16, 2018.
[13] M. S. Samarth Shah, "Deep Reinforcement Learning For Scalable Task Scheduling In Serverless Computing," Int. Res. J. Mod. Eng. Technol. Sci., vol. 3, no. 12, pp. 1845–1852, 2021, doi: DOI : https://www.doi.org/10.56726/IRJMETS17782.
[14] A. Goyal, "Enhancing Engineering Project Efficiency through Cross-Functional Collaboration and IoT Integration," Int. J. Res. Anal. Rev., vol. 8, no. 4, pp. 396–402, 2021.
[15] V. Hazarika and Akaash & Anju, "Extreme Gradient Boosting using Squared Logistics Loss function," Int. J. Sci. Dev. Res., vol. 2, no. 8, pp. 54–61, 2017.
[16] A. Lior, "Insuring AI: The role of insurance in artificial intelligence regulation," Harv. JL \& Tech., vol. 35, p. 467, 2021.
[17] Venkateswaranaidu Kolluri, "A Thorough Examination of Fortifying Cyber Defenses : AI in Real Time Driving Cyber Defence Strategies Today," JETIR - Int. J. Emerg. Technol. Innov. Res. (www. jetir. org), ISSN, p. 32, 2016.
[18] N. Boodhun and M. Jayabalan, "Risk prediction in life insurance industry using supervised learning algorithms," Complex Intell. Syst., 2018, doi: 10.1007/s40747-018-0072-1.
[19] L. T. Lai, J. Y. Wu, and L. M. Tseng, "The ethical decisions of life insurance salespeople: the effects of interest conflicts, ethical leadership and ethical training," J. Financ. Regul. Compliance, 2021, doi: 10.1108/JFRC-01-2021-0001.
[20] M. R. Islam et al., "Discovering dynamic adverse behavior of policyholders in the life insurance industry," Technol. Forecast. Soc. Change, 2021, doi: 10.1016/j.techfore.2020.120486.
[21] M. Kgare, "Predicting Lapse Rate in Life Insurance Using Machine Learning Algorithms," 2021.
[22] D. A. Rusdah and H. Murfi, "XGBoost in handling missing values for life insurance risk prediction," SN Appl. Sci., vol. 2, no. 8, pp. 1–10, 2020, doi: 10.1007/s42452-020-3128-y.
[23] W. F. Mustika, H. Murfi, and Y. Widyaningsih, "Analysis Accuracy of XGBoost Model for Multiclass Classification - A Case Study of Applicant Level Risk Prediction for Life Insurance," in Proceeding - 2019 5th International Conference on Science in Information Technology: Embracing Industry 4.0: Towards Innovation in Cyber Physical System, ICSITech 2019, 2019. doi: 10.1109/ICSITech46713.2019.8987474.
[24] M. H. Kotb and R. Ming, "Comparing SMOTE family techniques in predicting insurance premium defaulting using machine learning models," Int. J. Adv. Comput. Sci. Appl., vol. 12, no. 9, 2021.
[25] J. X. Lim and H. Kang, "A Comparison of Classification Models for Life Insurance Lapse Risk." 2019.
[26] N. Kumar, J. D. Srivastava, and H. Bisht, "Artificial intelligence in insurance sector," J. Gujarat Res. Soc., vol. 21, no. 7, pp. 79–91, 2019.
[27] J. H. B, "Risk Level Prediction of Life Insurance Applicant using Machine Learning," Int. J. Adv. Trends Comput. Sci. Eng., vol. 9, no. 2, pp. 2213–2220, 2020, doi: 10.30534/ijatcse/2020/199922020.
[28] N. Dhieb, H. Ghazzai, H. Besbes, and Y. Massoud, "A Secure AI-Driven Architecture for Automated Insurance Systems: Fraud Detection and Risk Measurement," IEEE Access, 2020, doi: 10.1109/ACCESS.2020.2983300.