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Research Article

Artificial Intelligence Technologies in Predicting Life Insurance Premiums: A Case Study on the Iraqi General Insurance Company

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ARTICLE INFO	ABSTRACT

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The insurance sector relies on considerable amounts of data and statistics where standard actuarial computations form the basis for determining risks, liabilities, and appropriate premiums. The traditional methods make predicting life insurance premiums complex task and less efficient. This affects the overall cost and development of proper insurance solutions. However, the rapid development of artificial intelligence technologies presents great opportunities to reshape traditional processes to improve efficiency and accuracy within the insurance industry. The presented work focuses on applying artificial intelligence in developing actuarial calculations, aiming to find a better estimate of the life insurance premium and providing better quality reports for the Iraqi General Insurance Company. In the current study, we used three machine learning algorithms, namely XGBoost, Random Forest (RF), and Decision Tree (DT), to analyze the collected data and estimate the life insurance premium. Different regression evaluation metrics, including MAE, RMSE, R^2, and Adjusted R^2, were applied in testing the performance of the algorithms. The results from the experiments showed that the XGBoost algorithm was the highest performing compared to other algorithms that recorded the lowest MAE and the highest R^2 score. The research also suggested that incorporating artificial intelligence techniques into actuarial analysis can enhance financial reporting efficiency, thus increasing insurance companies' competitiveness in the important sector. Consequently, Iraqi insurance companies need to adopt such technologies to face the changing insurance conditions by training employees and adopting digital transformation to stay competitive and benefit from innovation.

Keywords: Life Insurance Premiums, Iraqi General Insurance Company, Artificial Intelligence, Machine Learning, Actuarial Calculations.

INTRODUCTION

The Iraqi general insurance company is one of the essential financial institutions that face increasing challenges in enhancing the quality of financial reporting and advancing actuarial accounts. To keep pace with rapid developments in the business world, the use of artificial intelligence emerges as an innovative solution to improve financial analysis and prepare accurate and transparent reports, which contributes to enhancing confidence in the insurance sector and meeting the needs of beneficiaries. As the need for insurance rises, adopting technology and artificial intelligence in data analysis helps companies meet future customer needs, improve their preparedness for change, and help in strategic decisions that prepare them for change and innovation (Gentner et al., 2018).

Modern technologies have contributed to the progress of various fields; accounting information has become one of the basic tools in the field of information and technology, which not only focuses on financial controls but also has had a tremendous impact on the measurement of performance management (Al-Delawi and Ramo, 2020).

Artificial intelligence technologies are still relatively new to the insurance industry. The heavily regulated sector environment requires that AI systems be transparent, dependable, and highly accurate. To meet compliance standards, they must also fit into existing regulations and adapted requirements (Gramegna and Giudici, 2020).

The industry 4.0 revolution in the digital age is influenced significantly by artificial intelligence, which enables machines to gain knowledge through experience, adapt to new input data or information, and execute like a human being performing tasks.

These new technologies can process big data, and therefore, they allow us to recognize data patterns better (Miller, 2019), (Dagunduro et al., 2023) (Falana, Igbekoyi, and Dagunduro, 2023). Traditional models and techniques are still heavily and commonly used in actuarial science. With this, there is a growing trend around using artificial intelligence to incorporate into modern study methodologies as machine learning models, like LIME, CHAP, and partial dependence schemes (PDPs), start to emerge (Lozano-Murcia et al., 2023).

Due to the rise of big data technologies, actuaries have access to a greater volume of complex data. While conventional actuarial approaches have served the sector in the past, actuaries have not been trained to work with the huge amounts of unstructured data that arise today. Actuaries can take advantage of this by switching to new methods to process data in a more efficient and effective manner (Balona, 2023), as they can utilize the last methods and tools to analyze, estimate, and manage risks more efficiently, which helps develop the insurance and finance industry as a whole (Abbad et al., 2019).

The interest in machine learning technologies and big data models shows the importance of keeping up with technological developments in this field and thinking about how to best apply them in the insurance field to improve pricing and risk management (Blier-Wong et al., 2020). The current focus of actuarial work in artificial intelligence is primarily on the development of artificial intelligence agents that can perform specific tasks that may be difficult for a human actuary to complete efficiently. Certain tasks are challenging to accomplish without artificial intelligence due to their complexity and the significant time and effort they require (Yeo et al., 2019) ;with the growing need for financial reporting and persistent liquidity challenges, actuaries are faced with the need more than ever, to provide accurate calculation of premium and reserves (Mahohoho, Chimedza, and Matarise, 2023).

Machine learning (ML) is a sub-branch of artificial intelligence that shares similarities with actuarial science as machine learning encompasses a variety of knowledge and is combined to generate new outcomes. Machine learning has multiple methods and neural networks approaches to enable machines to improve their performance from experience and can be divided into three main categories (Sutton and Barto, 2018) (Kaplan and Haenlein, 2019), "supervised learning," "unsupervised learning," and "reinforcement learning". The researchers see the applied study and completion of research tasks and the development of actuarial calculations through the use of artificial intelligence as falling under the group of supervised learning. Algorithms build models using a sample of a data set that the computer is "trained" to absorb to make decisions based on it; hence, machine learning can improve itself without human intervention (Foote, 2019).

One of the main objectives of this research is to integrate contemporary artificial intelligence techniques into actuarial modeling to increase the precision and reliability of the life insurance business. The study showed that the use of modern technologies such as artificial intelligence can significantly improve calculation and forecasting processes in the field of insurance, which enhances accuracy and efficiency in this vital sector and thus reflects on improving the quality of financial reports.

The rest of the paper is structured as follows: Section 1 explores some literature review and related works. Section 2 provides the proposed methodology for using artificial intelligence algorithms to predict life insurance premiums, focuses on preprocessing the data, and features engineering. Section 3 presents the exploratory analysis of the selected dataset. Section 4 shows the present experimental results. Section 5 discusses and analyses the primary findings obtained from the results. Finally, Section 6 concludes the work by outlining potential directions for future work.

LITERATURE REVIEW

This section outlines and focuses on information exploration and the use of Artificial intelligence technologies in insurance premium prediction. Researchers have used different Artificial intelligence algorithms to analyze data and predict insurance premiums.

The study of (Alcaide, D.C. and Gonçalves, 2023) addressed the use of ML techniques to improve the accuracy of predicting life insurance policy cancellations, with the aim of helping insurance companies retain customers and avoid financial losses. The dataset that was used was collected from a questionnaire pertaining to both policyholders and historical lapse patterns. Various machine learning algorithms were employed to test their effectiveness. They found that Extreme Gradient Boosting and C5.0 algorithms recorded the highest results. Additionally, the study identified the main characteristics of customers and policies with high predictive power. The study has demonstrated knowledge and contribution to enhancing risk management practices in the life insurance industry.

However, the study conducted by (Kiermayer, 2022) shows that ML and DL can be used to deal with the current insurance actuarial challenges (contract aggregation, compliance analysis, and Markov chain calibration) and how ML can be used to solve pricing and customer risk of withdrawal problems, among others. They applied modern techniques such as neural networks, RF and XGBoost as ML examples to enhance traditional models such as the Generalized Linear Model. The study results showed how deep learning can have a crucial role in addressing rare events such as customer withdrawal, improving the accuracy of forecasts, cutting down on computational costs, and helping develop operations and capital efficiency in the insurance sector.

The study (Szepesváry, 2022) focused on how technology and quant methods changed the shape of the insurance industry by refining its cash flow modeling and pricing process. This study examined the use of simulation techniques such as Monte Carlo simulation and time series analysis in life insurance to analyze investment returns, mortality, and customer behavior. The study also explored related challenges of pricing non-life insurance premiums and estimating claims using machine learning algorithms, like Neural network approaches and Random Forests algorithms. The study concluded that technology improves model accuracy, pricing effectiveness, and understanding of customer behavior, enhancing the insurance industry's efficiency and development.

Similarly (ul Hassan et al., 2020) explored the use of ML techniques to estimate the premiums of health insurance, which remains a problem in the healthcare sector that is facing huge challenges. The research aims to test the performance of nine machine learning algorithms, namely linear regression, support machine regression, linear regression scale, Stochastic Gradient Boosting (SGB), XGBoost, declarative trees, Random Forests, multiple linear regression, and nearest neighbors in a computational intelligence approach. The results indicated that SGB performs better with an accuracy level of 86%, a simple feature of a cross-validation value of 0.858, and an RMSE of 0.340. The research demonstrates the necessity of applying machine learning techniques to enhance financial forecasting in the health insurance application domain and activity aimed at achieving more precise models in the future.

Additionally, (Zarifis and Cheng, 2023) explored business methods stemming from the insurance business by presenting AI and data technologies and the expected insurance business models for utilizing these technologies and their experimental verifiability. They applied AI-based automation in 20 insurance companies and considered a four-tier model for adopting AI technologies. The study demonstrated how AI became used to enhance processes and model business by embracing a sustainable digital transformation for efficiency. Moreover, the results showed that this transformation is necessary, and the right time to deploy this transformation is now, which speeds up the development of AI-powered insurance companies.

On the other hand (Yeo, 2017) examined the impact of intelligent technology and machine learning on the transformation of the actuarial industry, explaining that the insurance industry is not isolated from technological advances. The study indicated that intelligent technology will radically change the insurance industry over the next decade, with the performance of actuaries improved rather than replaced. The study also indicates that automation will allow actuarial work to be carried out more quickly and accurately, allowing actuaries to emphasize value-added activities such as risk management and business improvement. However, actuarial judgment remains necessary at all process stages, such as modifying data, making assumptions, and selecting methods, reflecting the continued importance of the human role.

The study (Looft, 2024) was also put forward with the question: Is machine learning a threat to the actuary's career? Through an overview of three possible scenarios for the future of actuarial science under the "AI Revolution," as it was referred to, one of these scenarios is based on the hypothesis that AI and ML, as it describes how technology can learn and improve at a rate far beyond human capabilities, and how actuarial forecasting methods developed by technology "do not age or decline in performance over time.

In the study (Gentner et al., 2018), in light of the application of ML algorithms, AI technologies could contribute significantly through strategic foresight in improving accounting and decision-making processes in organizations by analyzing data quickly and accurately. AI technologies can provide valuable strategic insights that help organizations improve their performance and achieve their goals more efficiently. This shows how AI has become an essential tool in accounting and data management in modern times.

PROPOSED METHODOLOGY

This work develops an artificial intelligence (AI) model using a machine learning (ML) algorithm to predict the life insurance premium for the Iraqi general insurance company.

As outlined in Figure (1), the proposed methodology begins with the data collection stage, which is considered the essential stage of any machine learning model. This work used the actuarial dataset from the Iraqi general insurance company. The selected dataset is then organized in a CSV file. The dataset is composed of 5736 rows and 11 columns, as shown in Table 1.

The aim of using AI algorithms is to predict the life insurance premium based on several input factors such as (Age, Insurance Duration, Insurance Amount, Payment Method, Additional Life Premium for Occupation, Additional Life Premium for Accidents, Additional Life Premium for Weight, Additional Life Premium (Illness) for 5 Years, Additional Life Premium (Illness) for 10 Years, Premium). We performed multiple preprocessing steps, such as removing duplicate items, checking for null values, and converting categorical inputs to numerical representations, as AI models cannot deal with categorical inputs directly without prior conversion.

The outlier detection process was conducted on the numerical variables of the dataset to remove the outliers and to ensure that all values were within the accepted Kurtosis and skewed values, as depicted in Table 2. This approach proved effective in maintaining model interpretability while enhancing its performance. Figure 2 shows the dataset summary statistics of numerical variables. The total dataset was separated into two subsets: training and testing data. About 70% of the dataset was selected for the task of training, while the remaining 30% was selected for testing, as shown in Table 3. The feature engineering step in our proposed methodology involves the following steps. First, the input features are normalized using the scaling method, which scales all the features in the training data set with the same range. This helps to avoid the concentration of some important features in one region of the model. Furthermore, polynomial features were used to create interaction and higher-degree terms that allow the model to identify many feature interactions. It also specifies how these techniques increase the efficiency and robustness of the modeling process while addressing the linearity or non-linearity of the relation between the characteristics and the dependent variable.

The current methodology establishes multiple regression algorithms with optimization methods, GridSearch for hyperparameters tuning, and 5-fold cross-validation technology to check the models' generalization to improve the prediction model's capability and reduce the chances of overfitting. The models include DT, RF, and XGB. The models were selected based on their impact on managing various data types and their connections.,. Finally, the algorithms are evaluated to check the performance using different evaluation methods: Mean Absolute Error (MAE), R squared (R^2), Root Mean Square Error (RMSE), and Adjusted R^2, to determine model performance.

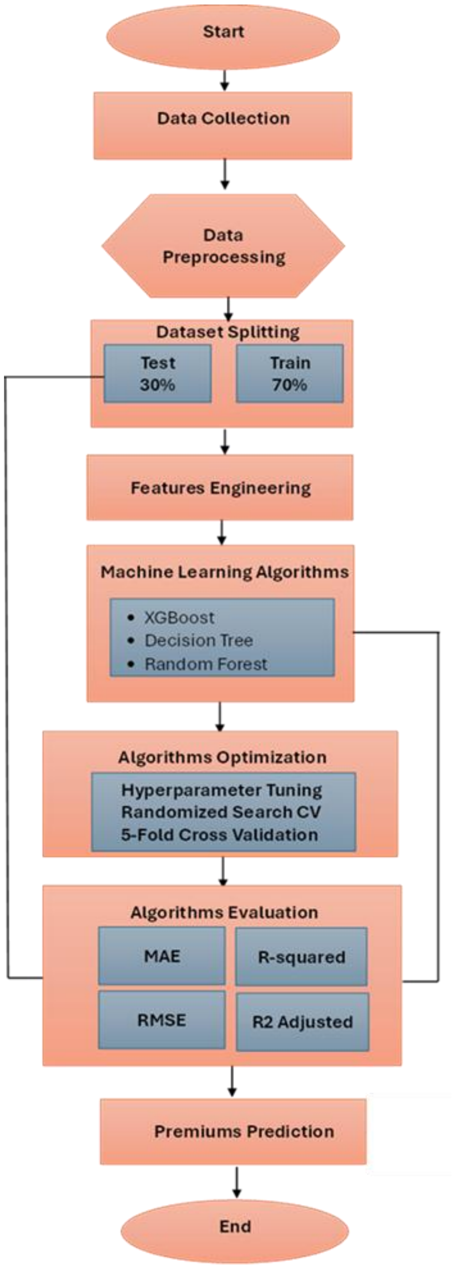

Figure (1): Proposed AI methodology architecture

Table 1: Overview of the Dataset

Input Name	Data Type
Age	Numerical
Insurance Duration	Numerical
Insurance Amount	Numerical
Payment Method	Categorical
Additional Life Premium for Occupation	Categorical
Additional Life Premium for Accidents	Categorical
Additional Life Premium for Weight	Categorical
Additional Life Premium (Illness) for 5 Years	Categorical
Additional Life Premium (Illness) for 10 Years	Categorical
Premium	Numerical

	Age	Insurance duration	Insurance amount	Premiums
count	5736.000000	5736.000000	5.736000e+03	5.736000e+03
mean	40.159170	5.207985	5.250000e+06	5.968801e+05
std	14.687027	2.730016	2.829090e+06	4.330760e+05
min	8.000000	1.000000	1.000000e+06	1.000820e+05
25%	28.000000	3.000000	3.000000e+06	2.454064e+05
50%	40.000000	5.000000	5.000000e+06	4.252674e+05
75%	52.000000	7.000000	7.000000e+06	8.761928e+05
max	68.000000	10.000000	1.000000e+07	1.820344e+06

Figure (2): Descriptive statistics of dataset numerical variables

Table (2): Statistical analysis of Skewness and Kurtosis of numerical variables

Numerical Feature	Kurtosis	Skewness
Age	-0.890	-0.048
Insurance Duration	-1.100	0.175
Insurance Amount	-1.093	0.232
Premium	-0.178	0.894

Table (3): Show the training and testing dataset samples

Total samples	Training Dataset 70%	Test Dataset 30%
5736	4015	1721

EXPLORATORY DATA ANALYSIS (EDA):

Figures (3,4,5,6,7) illustrate the exploratory data analysis of the input features of the selected life insurance dataset.

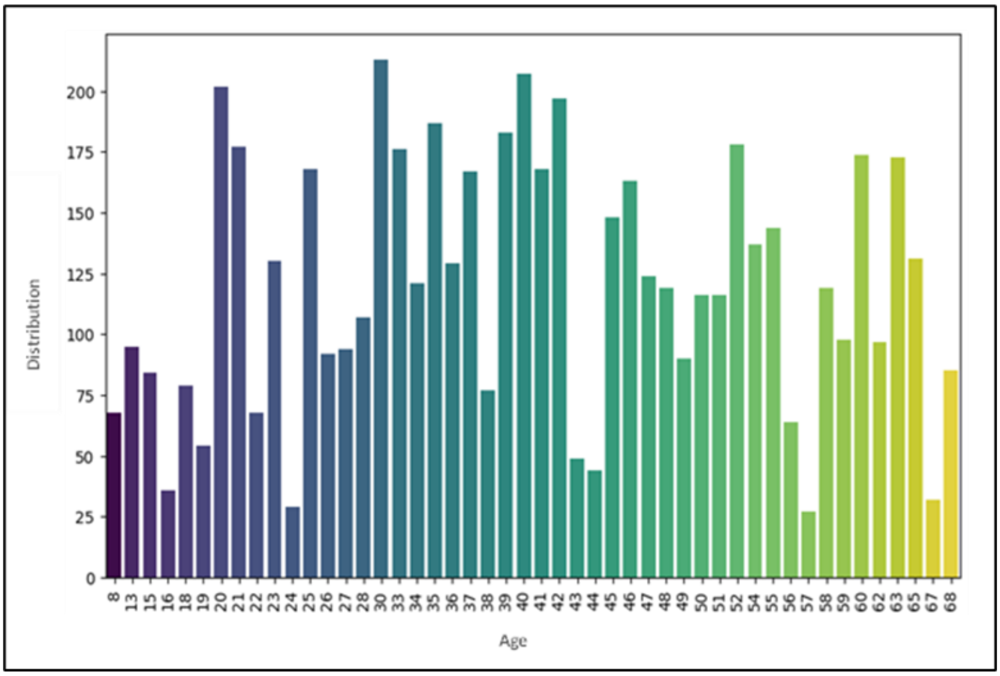

Figure (3): Age distribution

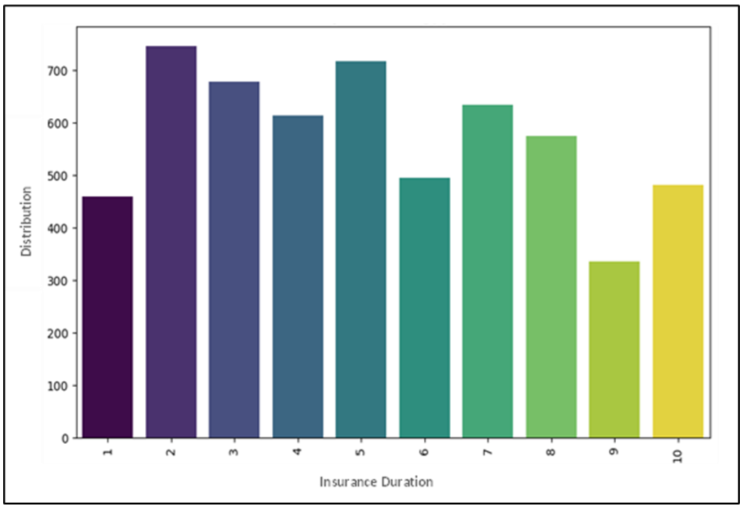

Figure (4): Insurance period distribution

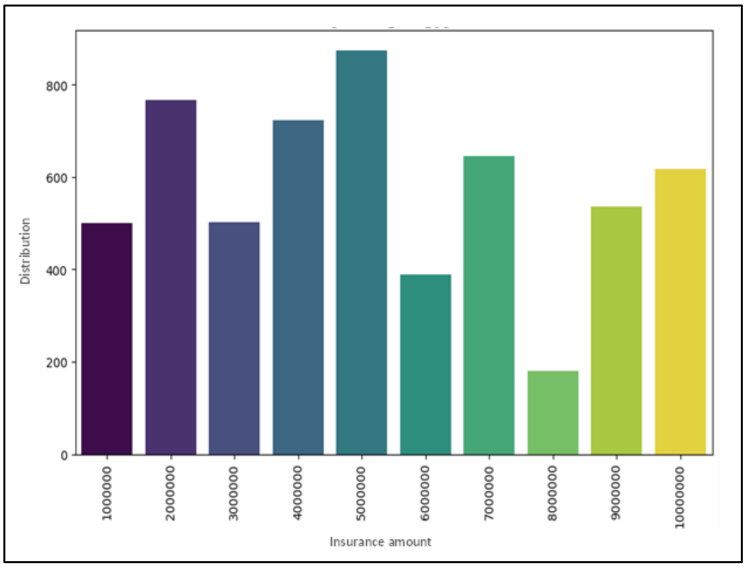

Figure (5): Insurance amount distribution.

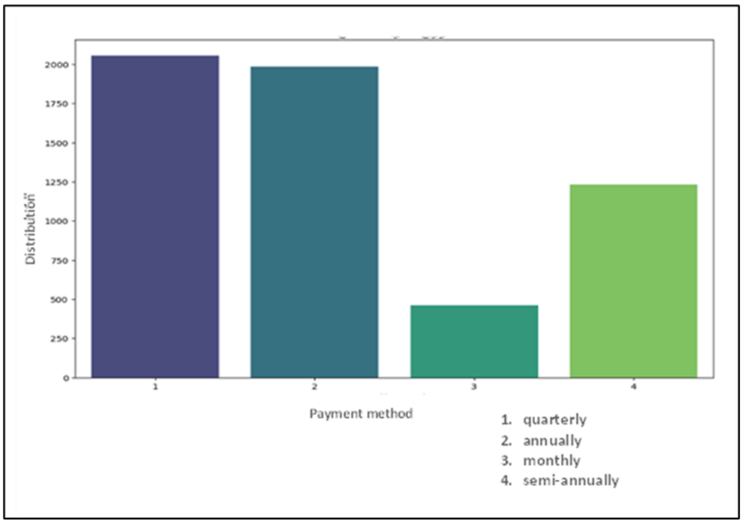

Figure (6): Insurance Payment Method Distribution.

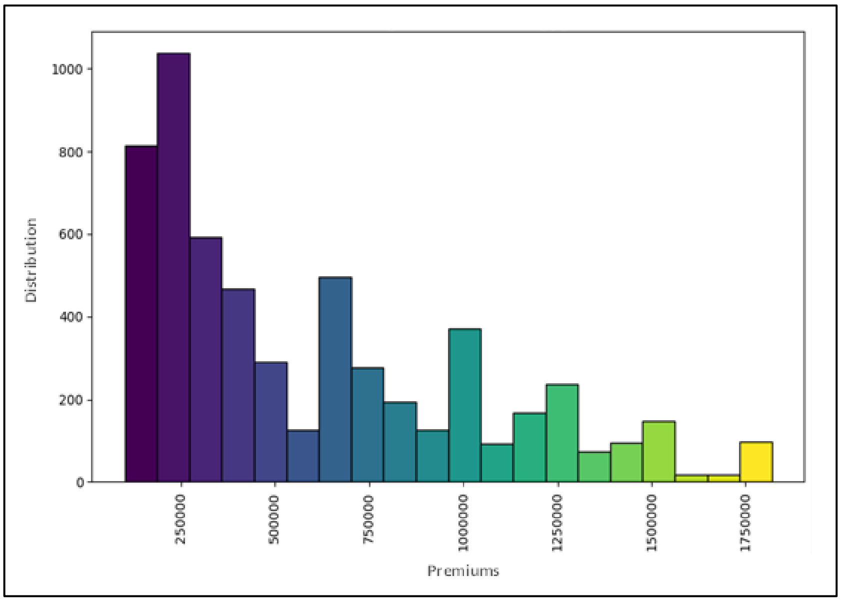

Figure (7): Life insurance premiums distribution.

EXPERIMENTAL RESULTS

4.1 Regression Evaluation Metrics:

The use of artificial intelligence in developing life insurance predictions can be tested by evaluating the efficiency of the algorithms used. The first step in evaluation is to use well-known prediction performance metrics such as Chicc et. al., 2021). Four evaluation methods were applied in the present work, including R^2, MAE, RMSE, and Adjusted R Squared.

- **R Squared (R^2):** Measures the strength of the relationship between expectations and actual values and gives an idea of the percentage variation in the transponder variable that the model can explain. It can be calculated as shown in Formula 1.

$$R^2 = 1 - \frac{\Sigma(Y_i - \hat{Y}_i)^2}{\Sigma(Y_i - \bar{Y})^2}$$

Where: Yi is the actual values, Ȳi is the predicted values, and Ȳ is the mean of actual values.

- **Mean Absolute Error (MAE):** Measures the average absolute values of errors between predicted and actual values and gives an idea of the overall average of errors without regard to their direction. It can be calculated as shown in Formula 1.

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \tag{2}$$

Where Yi is the actual values, Ŷi is the predicted values, and n is the number of observations.

- **Root Mean Square Error (RMSE):** This error is evaluated by taking the root mean squared values of errors, which gives more weight to large errors and is useful for understanding how the model performs under various conditions. It can be calculated as shown in Formula 3.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{3}$$

- **Adjusted R Squared:** Used to measure how well regression model predictions are relative to actual values. It can be calculated as shown in Formula 4.

$$\text{Adjusted } R^2 = 1 - \left(1 - R^2\right) \times \frac{(n-1)}{(n-p-1)} \tag{4}$$

Where: R^2: The coefficient of determination, with n being the number of observations and p representing the number of independent variables (predictors).

4.2 Models Evaluations

We applied multiple evaluation metrics, including MAE, RMSE, R Squared, and Adjusted R^2 metrics, as shown in Table 4, to measure the model's performance of the AI algorithms used in our methodology. From the empirical results, we noticed that the XGBoost algorithm gave higher results than other algorithms, as it recorded the lowest values in the MAE. This accuracy extends to the RMSE method as well, emphasizing the low error within the model predictions and the actual values, as well as the error rate, and as noted, the R^2 of 0.99608 in the testing phase was the highest among the models, demonstrating the power of XGBoost in explaining the variance within the data.

On the other hand, the Decision Tree algorithm showed limitations in dealing with the complexity of the data, and although the Decision Tree models were easy to interpret, this feature was not accurate enough compared to the other algorithms used to compensate for the lack of accuracy recording a value of R^2 0.98943

On the other hand, the Radom Forest algorithm gave improvements to the Decision Tree model using aggregation technology, providing a performance improvement, and the MAE scored the test with a value of 14772 and R^2 with a value of 0.99597, indicating an improvement in accuracy, but without being able to surpass XGBoost. RMSE assessments also showed improvement over Decision Tree. Figure 8 shows MAE, RMSE, R^2, and Adjusted R^2 results of AI regression algorithms for training and testing datasets. These results were obtained after applying the three algorithms created to evaluate the models and show the differences between the algorithms while clarifying the proximity of the predictions to the actual values across trend lines and data points. From comparing the models, it's clear that XGBoost stands out for its accuracy and ability to handle life insurance data effectively. Table 5 shows the best parameters for hyperparameter tunning identified within the machine learning algorithms used in XGBoost, DT, and RF to improve the effectiveness of each algorithm when used to predict the premium value in linear regression. Based on the results and analysis, the outputs of the applied machine learning models are further clarified through visual representation. The scatter plot illustrated in Figure 9 shows the correlation between actual and predicted values using the best model of XGBoost regression.

Table 4: Performance evaluation of regression algorithms

Algorithm	Training/Testing	MAE	RMSE	R^2	Adjusted R^2
XGBoost	Training	14252	25978	0.99645	0.99644
	Testing	14434	26600	0.99608	0.99608
Decision Tree	Training	22832	37550	0.99258	0.99256
	Testing	25500	43753	0.98943	0.98943
Random Forest	Training	14467	26329	0.99635	0.99634
	Testing	14772	26966	0.99598	0.99597

Table 5: Shows the best-optimized parameters of different AI algorithms

Model	Best Parameters
XGBoost	Regressor-subsample:0.9 Regressor-n_estimators:3000 Regressor-max_depth:5 Regressor-learning_rate:0.05 Regressor-colsample_bytree:0.8
Decision Tree	Regressor-min_samples_split: 2 Regressor-min_samples_leaf':1

	Regressor-max_depth:8
Random Forest	Regressor-n_estimators:1000 Regressor-min_samples_split:5 Regressor-min_samples_leaf: 1 Regressor-max_depth':None Regressor-bootstrap': True

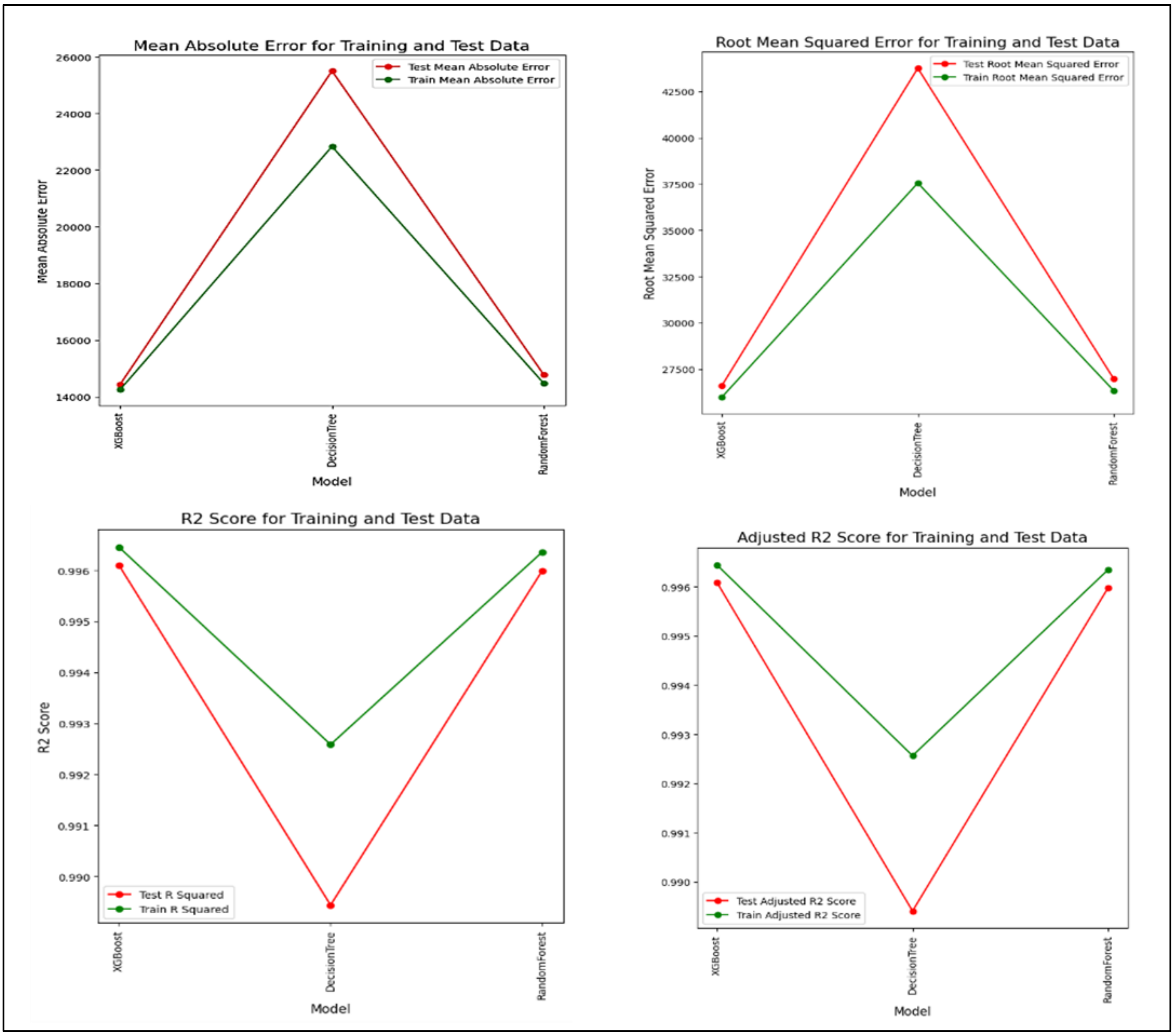

Figure (8): Shows MAE, RMSE, R^2, and Adjusted R^2 results of AI algorithms for training and testing dataset

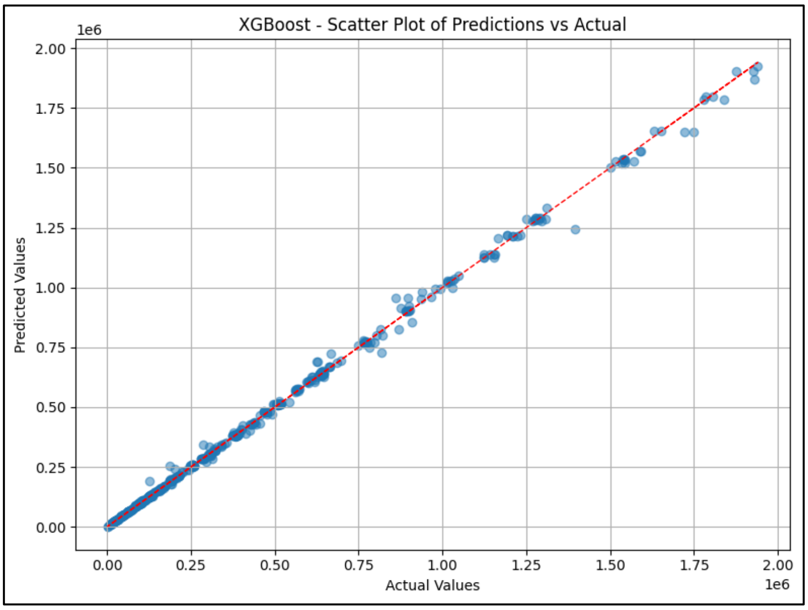

Figure 9: Regression Line of Actual and Predicted Values Using XGBoost Algorithm.

DISCUSSIONS

The empirical results indicate that the XGBoost model performed better in predicting life insurance prediction. XGBoost model also captured the intricate relationship between the features in the data since the model had a higher R^2 with lower RMSE and MAE scores. On the other hand, traditional models like DT and RF show a higher degree of error, and it is marked that this model has higher deviations from actual values because of their inability to look at the non-linearity and interaction in the dataset. The experimental results also highlight that hyperparameter tuning is an effective optimization method for enhancing model performance. Further, the findings also reveal that the models are not overfitting and have low variance, whereas those are quite important while dealing with the complexity of real-time medical insurance data to predict the premiums accurately. However, this present study is limited by the dataset used. This paper also highlights future research directions that may include extending the identified models to larger and more diversified datasets, including a broad spectrum of life insurance systems and more geographical areas. However, it is recommended that an ensemble model be created according to the final results of this study to increase the levels of accuracy and generalization.

CONCLUSIONS AND FUTURE WORK

Life insurance premium prediction is challenging due to many factors that impact accurate prediction. A vital aspect of this process is the efficient collection and preprocessing of data. In this work, the life insurance dataset from the Iraqi general insurance company was used to train and test various ML algorithms and compared to identify the one best suited to the selected dataset., including DT, RF, and XGB Regressors. The regression process for the chosen dataset involved several steps: preprocessing, feature engineering, data splitting, regression model deployment, and evaluation. Our results demonstrate that our proposed methodology using machine learning for life premium prediction is effective and capable of producing results comparable to other life premium prediction models. According to the obtained results of the model's assessment, it was found that the XGBoost model performed higher compared to other algorithms, recording the lowest values of the test set error ratio, indicating its high accuracy in predictions and providing the highest value of testing R^2 of 0.99608. The research found that employing modern technology, specifically AI, to develop actuarial calculations is an essential step towards improving calculations and predicting in the insurance sector, as the study shows that the use of modern technologies such as AI can significantly improve calculations and forecasting operations in the field of insurance, which enhances accuracy and efficiency in this vital sector, and thus reflected in improving the quality of financial reports. However, future research can be conducted further by testing experiments with more datasets, including extra feature extraction methods and data from different insurance companies, and exploring different AI models. This work can also enable the designing a software interface based on AI to predict the life insurance premiums for users' external data input for the Iraqi general insurance company. These efforts will help guarantee that the AI models can be reliable and expandable, provide more accurate predictions in various conditions, and thus contribute to increasing the availability of affordable life insurance services globally.

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