Study on postal life insurance attributes and its growth prediction using machine learning algorithms

Thangavelu Ananadaraj Rajasekaran, Pichamuthu Vijayalakshmi, Velayutham Rajendran
Department of Electronics and Communication Engineering, Vels Institute of Science, Technology and Advance Studies (VISTAS), Chennai, India

Article Info

Article history:

Received Jun 19, 2024
Revised Oct 8, 2024
Accepted Oct 30, 2024

Keywords:

Logistic regression
Machine learning
Prediction
Random forest
Supervised learning
Support vector machine

ABSTRACT

The oldest insurer in the country, since 1884, is Postal Insurance. For today's livelihood, the citizens of India's life-saving coverage and insurance have become necessary. For customers to overcome difficult situations, life insurance is crucial in creating confidence. This is one of the highlights of the Postal organization. Under postal life insurance (PLI), the volume of new policies is enrolled throughout India, and a supervised machine learning (ML) process for finding the business cluster is carried out based on this data, which is discussed. A ML algorithm that predicts the growth for the future, using a suitable algorithm for accessing the features and process to identify the prediction model, has been developed, which is the main goal of this study. Simulation results show that expected is one of the most important variables used to predict and that both random forest (RF) and logistic regression outperformed the other two models. The RF model is the most effective and fastest in predicting the system's future state, and it shows the highest value for the PLI product.

Corresponding Author:

Thangavelu Ananadaraj Rajasekaran
Department of Electronics and Communication Engineering
Vels Institute of Science, Technology and Advance Studies (VISTAS)
Chennai, Tamil nadu, India
Email: tarajasekaran@gmail.in

1. INTRODUCTION

Beneficiaries of life insurance are safeguarded in the case of an unplanned incident or accidental death. However, the demand for life insurance is often modest in nations with well-established social security systems [1]. Purchasing a life insurance policy is heavily influenced by one's views on life insurance and perceptions of mortality risk. The financial risk associated with death is known to most families. However, this doesn't result in their buying life insurance, which might impact how long their funds can last. United States Postal Life Co [2]. Initiated in 1884 for the benefit of postal workers, postal life insurance (PLI) was subsequently expanded to include the Department of Telegraph in 1888. It now extends to local and autonomous bodies, universities, government-aided schools, nationalized banks, credit cooperative societies, joint ventures with at least a 10% government or public sector undertakings (PSU) stake, and other organizations. Members of the Paramilitary forces and the defense services, as well as their personnel, are further insured by PLI. With effect from 24.3.1995, the government granted permission to PLI to expand its coverage to rural regions for life insurance transactions. This decision was based on the extensive network of Post Offices in rural areas and the relatively cheap operating costs [3].

Every organization has an essential task in measuring growth performance periodically to check its demand and to improve its performance habitually to meet its target; in PLI sector the growth of the product is measured using the policies that have been enrolled periodically and branch-wise performance which can be portrait with the help of time series algorithm, a saving schemes platform's lifetime, including its product, growth, stability, and decline, may be better understood with the use of account opening prediction [4]. In recent years, machine learning (ML) has been suggested as a substitute approach in life insurance research, and in 2021, it was among the most popular subjects. However, most of past academics' ML research has been on non-life and life insurance lapses. Research indicates that big transactions often need more data and outliers that affect sales. To improve prediction accuracy, time series analysts combine and create new algorithms [5]. This study chose five supervised algorithms extra tree, autoregressive integrated moving average (ARIMA), random forest (RF), Lasso, and neural network. Based on the results of the forecasting, error testing has led to modern business study models route mean square error (RMSE) [6]. The research study was made in forecasting the sales of Walmart where different classification algorithm was used, and on comparison and test conducted using mean absolute error (MAE) and RMSE parameters of each model was obtained and based on the score high accuracy of the models were picked [7].

Another study was made on Amazon sales data. Two methods were used in the analysis to predict the use of reliable and known approaches thereby resulting in better accuracy; the study was conducted on three algorithms: Winters' exponential smoothing, time-series decomposition, and ARIMA. The results were measured using MAE and RMSE [8]. This study aimed to solve the challenge of finding the right model utilizing intelligence and data driven approaches, considering the business's knowledge of the situation. Finding out how useful and successful each model is was the driving force for this study [9]. All of this is done to ensure that the chosen approach is suitable for the chosen company environment [10]. Decision trees, neural networks, Naïve Bayes, RF, and support vector machines (SVM) were the algorithms used in this study. The results are being tabulated against the accuracy, depending on the method used. The following algorithms have the lowest scores: RF (85%), Naïve Bayes (83%), decision tree (76%), neural network 70%, and SVM 59%. Because of its high accuracy model (85%), RF is the best way to be picked [11].

The domain for this study is E-commerce. Starting a new approach to acquire and analyze data might have a major influence on a business since the result can be favorable or go the other way. E-commerce platforms capture vast amounts of data and store it in their data centers. It's reasonable that they won't want other firms to analyze their data for privacy reasons, but they can also form their own team to analyze the data, which may be lucrative for them [12]. Knowing when a future epidemic may occur, preventive efforts can be made to reduce its effect. Such preventative actions include vector management, public health messages to avoid high-risk behaviors or regions, and enhancing physician knowledge for early diagnosis and treatment. For such prevention to take place, early and precise prediction of epidemics is important [13]. They need to look at this as an advantage for their company's potential, such as examining the data and its pattern throughout the years. For example, all the client data from registration, search history, purchases, and conversations are saved on their server. They will only be accessed when there is an issue with current data [14]. Traffic prediction is integral to advanced traffic management systems (ATMSs) and advanced traveler information systems (ATISs). The federal highway administration (FHWA) encourages all traffic management centers (TMCs) to post-travel times and incident information, giving helpful information to motorists and supporting them in making route choice options. Such information may aid vehicles in choosing to divert from crowded roadways, thereby giving essential extra capacity and contributing to the management of congestion [15].

All the post office investment plans guarantee returns since the government of India backs them. Moreover, the post office investment plans give tax savings of up to Rs.1.5 lakhs upon investment. Customers may make use of the post office's many banking options. Building the most accessible, inexpensive, and trustworthy bank for the ordinary man is the primary goal, along with leading the charge to reduce costs and remove obstacles to financial inclusion [16]. With the decline of snail mail and the rise of more convenient electronic methods, postal operators are exploring new avenues for growth, such as financial services, insurance, and high-value retailing, by extending their network of post offices in creative ways [17]. A centralized military force was considered essential for many reasons, including quelling internal resistance to the new government, reclaiming complete sovereignty from Western powers, and safeguarding and advancing Japan's geopolitical interests in the area. Although there was universal agreement on the need for a national military, there was much debate over how to staff the forces. An essential problem with any mandatory military service system is the unfair distribution of the financial and emotional costs among draftees and their families [18]. An insurance company is a financial entity that offers protection against financial losses caused by future risks. If the insured incurs damages, the insurer has agreed to pay a certain sum [19].

A combination of factors, including the identification of critical aging biomarkers and the rising prevalence of impairment across all age groups, has brought attention to the connection between the risks of morbidity and death. An epidemiologic trend toward chronic, degenerative, noninfectious illnesses with disability migrating into middle adulthood was seen in economically developed nations by the mid-twentieth century. The association between risk factors (such as smoking, alcohol use, lack of exercise, food, or kind of job) and the result of mortality has been examined in several epidemiological research, especially longitudinal investigations. Continuous or recurrent monitoring of risk variables, health outcomes, or both is done in a longitudinal study over an extended period [20]. With 155,000 locations throughout the country, the Indian postal savings system is the largest savings bank in India. Even though India's economy has developed and now has other investment options, the Indian government continues to support this tried-and-true investment choice. Direct and indirect investments are the two main options for those who save at post offices. There are numerous institutions that investors have faith in, but only some can match the post office's stellar reputation for dependability [21]. A wealth of innovative services, including a tracking system, e-payment, e-post, book now pay later (BNPL), and many more, have been introduced by the department of India-post during the last decade to meet the demands of clients. The primary goal was to close the digital gap between India's urban and rural areas, particularly via new technologies. India post is likely one of the few government agencies in India that offers these low-cost and easily accessible services to rural areas [22].

Various institutions allow societies to safeguard themselves economically. They encourage individual savings or property ownership, shift risks onto public welfare organizations, or both. This suggests a security system that exposes more individuals to short-term volatility and risk [23]. A person should initiate legal action against their country in a national court if they believe a Council of Europe member state has infringed their human rights. They may take their case to the ECtHR after trying everything else in their country's courts [24]. Further, most studies on what factors influence customers' trust and pleasure have used either quantitative or qualitative approaches, neither of which may do justice to the phenomena's depth and complexity [25]. Concerns about pain management and other physical symptoms (such as shortness of breath, agitation, and secretions) that come with approaching death are common among patients and their family caregivers in end-of-life care. Another common issue is avoiding needless transfers to acute care institutions. Staff members at long-term care facilities are responsible for evaluating residents for symptoms of pain and discomfort and administering the proper prescriptions as part of a multidisciplinary team that includes physicians (and, in certain cases, nurse practitioners) who may prescribe end-of-life medications [26], [27]. Insurance risk evaluation, definition, classification, and pricing is underwriting. Because risk management is a part of it, it is crucial to the functioning of any insurance program [28].

Background: time series models may be very useful when predicting the efficacy of account opening for different modest saving products of the director of photography (DOP). Predicting future occurrences is possible with the use of incidence statistics [29]. It is now possible to evaluate the prediction ability of several time series models, thanks to advancements in modeling techniques, for example, to forecast the occurrence of H5N1 outbreaks in Egypt. In summary, RF time series modeling is superior in predicting the spread of infectious diseases compared to other time series models. This finding and others demonstrate the similarity between bird and human epidemics. It offers a fresh method for forecasting these potentially devastating outbreaks in bird populations using already-existing, publicly available data. The severity of highly pathogenic avian influenza (H5N1) outbreaks in Egypt follows a time-series pattern. Results: we found that the RF and logistic regression are the best methods for predicting the values for PLI data sets. Whereas the other models, ARIMA and SVC, have huge observation values of error w.r.t MAE and RMSE values, the best fit was likely to be observed in RF.

2. RESEARCH METHOD

This study used an ML technique to classify clients based on their features to predict the class label for potential consumers, regardless of whether they purchase a life insurance policy. It may help insurance firms choose prospective customers more carefully throughout the underwriting process. In addition, a more comprehensive understanding of the Indian target market may be obtained by looking at the descriptive analysis of the respondents' sociodemographic data, which might raise the nation's life insurance penetration rate. Because the dataset is unbalanced on a given class label, this study offers insight into forecasting by utilizing various sampling and ensemble approaches throughout the classification process using ML algorithms. The primary goal is to compare the four most common kinds of time series forecasting ML algorithms to get the most accurate prediction model for the provided data. Four classification models ARIMA, linear regression, SVC, and RF will be used in this work. Figure 1 illustrates the proposed methodology.

This figure explains how the dataset is connected to a supervised ML for calculating and transforming the time series. It is connected to two models: test model: from the time series transformation, the test model is sent for data validation. Train model: the training model is connected to fit the type of model learning. This is connected to the balanced dataset for predicting the model and validation.

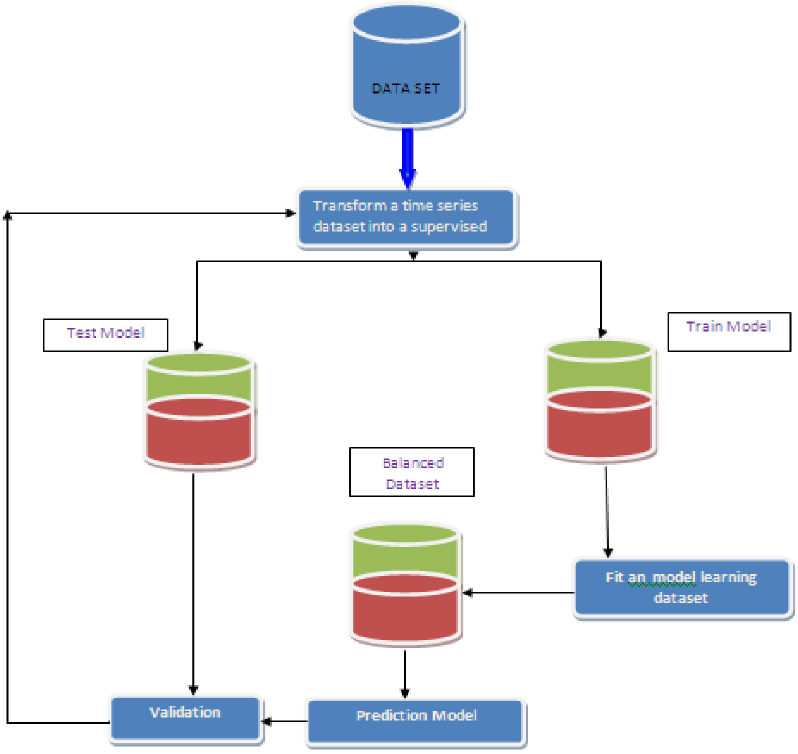

Figure 1. Research method

2.1. Data collection

PLI data and its monthly stats are posted daily on the site https://mis.cept.gov.in/CBS/Dbt_Dash.aspx and are regularly maintained by the Department of POST. The data collected in various aspects during the month has been streamlined and broken down into circle-wise and date-wise reports and consolidated on date-wise collection of the total number of policies successfully enrolled during August 2021 and September 2021. Pre-processing and training pre-processing and training.

2.2. Pre-processing and training

Accumulated data is in a common separate value format (CSV), and the data is imported into the Python platform 3.7.4 using the Juypter Notebook inbuilt version of Anaconda. We have transformed the time series data into a supervised learning data set. These data sets are split into train and test the samples where the models have been applied for the study to predict and forecast the values. This training process was applied to all models. The preprocessing of the data set and the stages it passes are depicted in Figure 2.

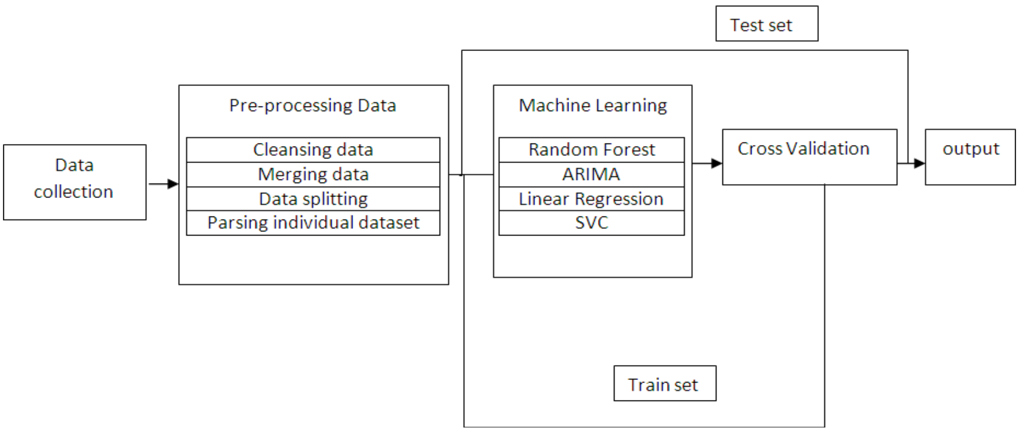

Figure 2. Training and pre-processing of data

2.3. Machine learning algorithms

RF model: a RF commonly known as a bagging algorithm in ML, where the 'n' number of trees are grown for the samples. In this model, the ensembles are fixed up to 1,000 trees, and the output data are evaluated using the RF model, making one-step forecasts for the given samples. The RF is a supervised learning method that can deal with issues about regression and classification. It acts as a collective by forming a forest, or numerous trees, to make choices. It offers precise forecasts for several uses. It can quantify the significance of every feature of the training dataset.

ARIMA model: ARIMA usually creates linear equations to solve time series forecasting problems. It is governed by three major parameters: auto-regressive (P), moving average (q), and integration or determining the order of differencing. An ARIMA (5,1,0) model was fitted initially. The auto-regression lag is set to 5, the time series is stationary with a difference order 1, and the moving average model is set to 0. Future time steps may be predicted using the ARIMA model. The ARIMA results object uses a predict () method to generate forecasts. It takes the time step index as an input and uses it to produce predictions. These indices are relevant to the beginning of the training dataset used for prediction purposes. Each detail is in a history database, initially filled with training data and updated with fresh details with each cycle. Here is a Python example of a rolling forecast using the ARIMA model to put it all together. Finally, we may determine the forecasts' RMSE.

Logistic regression model: assigning data to a discrete set of classes is the job of logistic regression, a classification procedure. Email spam vs. non-spam and online transactions are two instances of categorization issues. Would you rather have a benign tumor or a malignant one? Logistic regression uses the logistic sigmoid function to convert its output to get a probability value. Ordinal logistic regression allows for dependent variables to be of three or more potentially ordered sorts, such as "low," "medium," or "high.". We achieved our aim of visually representing the logistic regression training set results. Now, we can go on to the next classification: dividing data sets and training them to predict the values of the following twelve consecutive series accurately.

Support vector classification (SVC) model: the SVM is a linear model that may be used to solve regression and classification issues. It provides satisfactory solutions, whether linear or non-linear, for various real-world issues. A basic premise of SVM is that to categorize the data, the algorithm draws a line or hyperplane. All the training data will go into making predictions when we train the classifier with many data sets. Use the prediction technique to forecast the sample label. Figure 3 explains the SVM classification model. The mixed data is segregated using the SVM algorithm into class 1, 2, 3, 4. Some samples may be provided, and these details are given below:

Class 1: basic linear SVM
- Focus on binary classification with linear separability.
- Hard margin and soft margin approaches.

Class 2: Kernel-based non-linear SVM
- Extends SVM to handle non-linear separable data using Kernel tricks.
- Incorporates various Kernel functions for transformation.

Class 3: SVM for regression
- Adapts SVM methodology to regression tasks.
- Handles both linear and non-linear regression through appropriate Kernel selection.

Class 4: anomaly detection SVM (one-class SVM)
- Specializes in detecting anomalies within a dataset.
- Useful for applications like fraud detection, and network security.

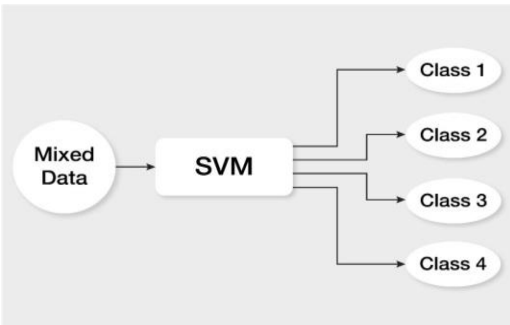

Figure 3. SVM classification model

3. RESULTS

Different performance comparisons were offered using the ML approach. The ML models' performance much raises that of the models. Several comparisons were utilized to evaluate the algorithms' ability to predict future outcomes. The RMSE and MAE are calculated; the MAE quantifies the typical size of forecasting mistakes, ignoring the direction of these errors. In the case of continuous variables, it assesses precision. The MAE and RMSE may take values between 0 and infinity, but the wider the gap between them, the more variation there is in the individual mistakes. Consequently, the RMSE will always be more or equal to the MAE. Less is more in this case. Accuracy measurement in predictions establishing metrics that enable the comparison of the various methodologies is vital for assessing the accuracy of the forecasts. The forecast outcomes must be compared to the predicted circumstances at the designated date, and a total number of accounts must be established as part of this assessment. Figure 4 shows the RF model output.

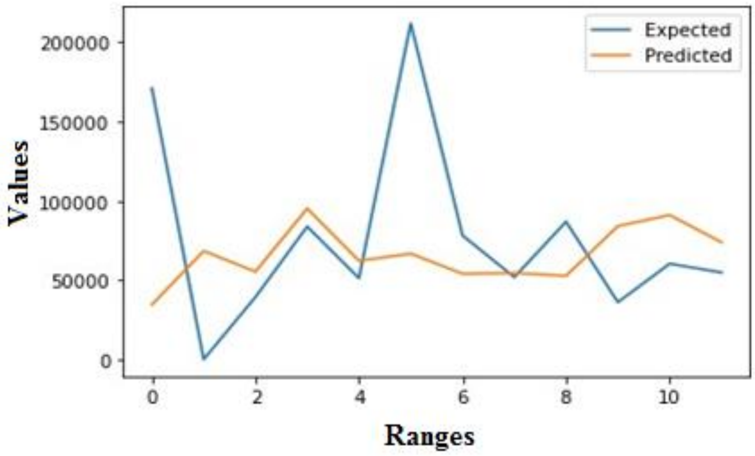

Figure 4. RF model output

The graph shows the expected range of (0-2), the value will be approximately 1 65,000; in the range of (2-4), the value will be approximately 70,000; in the range (4-6), the value will be approximately 2, 10,000, in the range of (6 -8) the value will be approximately 80,000, in the range of (8-10) the value will be approximately 60,000. The predicted range of (0-2) is 40,000; in the range of (0-4), the value will be approximately 90,000; in the range (4-6), the value will be approximately 60,000; in the range of (6-8) the value will be approximately 55,000, in the range of (8-10) the value will be approximately 80,000. Figure 5 shows the ARIMA model output.

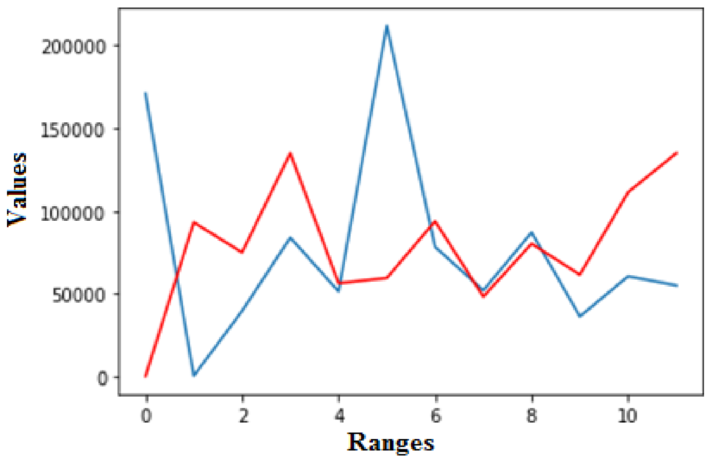

Figure 5. ARIMA model output

The graph shows the expected range of (0-2), the value will be approximately 1, 65,000; in the range of (2-4), the value will be approximately 70,000; in the range (4-6), the value will be approximately 2, 10,000, in the range of (6-8) the value will be approximately 80,000, in the range of (8-10) the value will be approximately 60,000. The predicted range of (0-2) is 40000; in the range of (0-4), the value will be approximately 90,000; in the range (4-6), the value will be approximately 60,000; in the range of (6-8) the value will be approximately 55,000, in the range of (8-10) the value will be approximately 80,000.

Figure 6 shows the logistic regression model output. The graph shows the expected range of (0-2), the value will be approximately 1, 65,000; in the range of (2-4), the value will be approximately 70,000; in the range (4-6), the value will be approximately 2, 10,000, in the range of (6-8) the value will be approximately 80,000, in the range of (8-10) the value will be approximately 60,000. The predicted range of (0-2) is 50,000; in the range of (2-4), the value will be approximately 1, 50,000; in the range (4-6), the value will be approximately 60,000; in the range of (6-8) the value will be approximately 1, 65,000, in the range of (8-10) the value will be approximately 2, 10,000. Figure 7 shows the SVC model output.

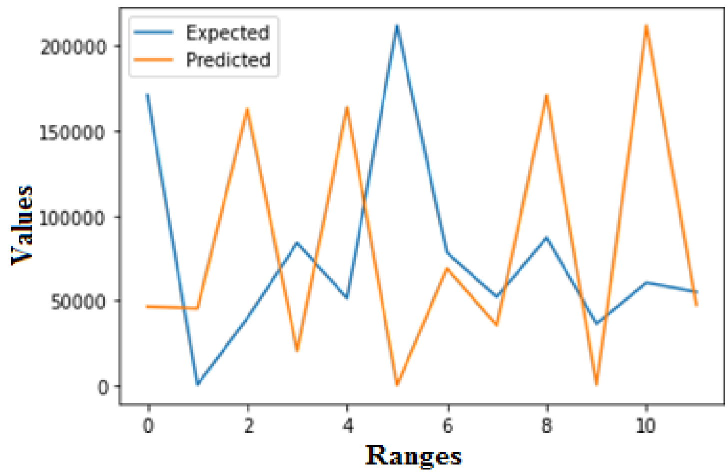

Figure 6. Logistic regression model output

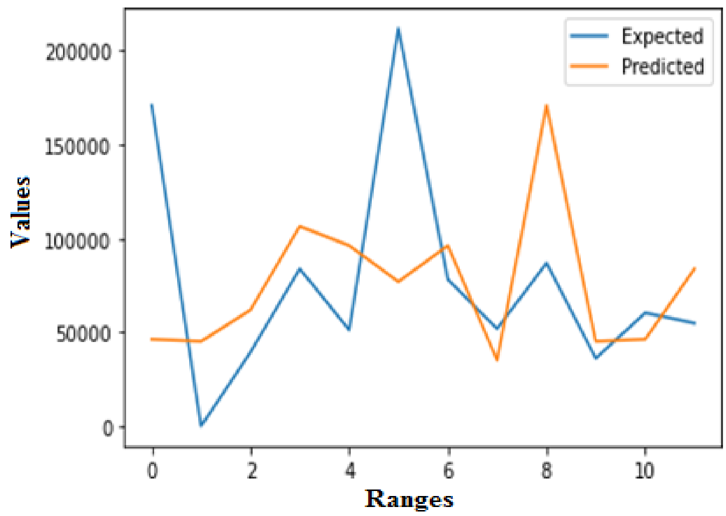

Figure 7. SVC model output

The graph shows the expected range of (0-2), the value will be approximately 1 65,000; in the range of (2-4), the value will be approximately 70,000; in the range (4-6), the value will be approximately 2, 10,000, in the range of (6-8) the value will be approximately 80,000, in the range of (8-10) the value will be approximately 60,000. The predicted range of (0-2) is 50,000; in the range of (2-4), the value will be approximately 1, 20,000; in the range (4-6), the value will be approximately 70,000; in the range of (6-8) the value will be approximately 45,000, in the range of (8-10) the value will be approximately 50,000.

MAE represents the average absolute difference between the predicted y^ and the true value y. This metric corresponds [30]. RMSE indicates the square root of the mean of the squared difference between the observed y and the predicted values y^ this metric corresponds. In (1) shows the MAE, and RMSE indicates 2. Predictions of MAE and RMSE using models of ARIMA, RF, logistic regression, and SVC are shown in Table 1.

$$MAE = \frac{1}{n}\sum_{j=1}^{n}\left|Y_j - Y^{\wedge}\right| \tag{1}$$

$$RMSE = \sqrt{\frac{1}{n\sum_{j=1}^{n}(Y_j - Y^{\wedge})}} \tag{2}$$

Table 1. MAE and RMSE of the ARIMA, RF, logistic regression, and SVC models forecasts

Model/product	MAE	RMSE
ARIMA	57,511	79,046
RF	45,560	64,685
Logistic regression	47,150	62,994
SVC	82,219	102,558

4. CONCLUSION

An efficient way to deal with distribution changes in the future environment was to do forecasts. Assuming the distribution varies slowly, we may train the models to filter out the noise. The conclusions of this essay will be advantageous to society as a whole since insurance protection is essential to the long-term viability and financial stability of families. Improving the underwriting process can aid the insurance company in choosing possible customers more efficiently. This research will also clarify the prediction by utilizing different samplings throughout the classification process using ML algorithms with an unbalanced dataset. Simulation results show that expected is one of the most important variables to predict and that both RF and logistic regression outperformed the other two models. The RF model, on the other hand, doesn't have a matching term as it uses linear assumptions about the connection between anticipated and predicted values. By compiling important information from relevant studies and offering practical suggestions for academics and financial analysts, this study adds to the body of knowledge in the field. The RF model is the most effective and fastest in predicting the system's future state, and it shows the highest value for the PLI product ad. In the future, we want to employ predictive algorithms that are well-suited to sector studies to extract data from the postal department's logistics services and benchmark and compare these algorithms with those of other competing organizations.

REFERENCES

[1] K. Karthika, S. Dhanalakshmi, S. M. Murthy, N. Mishra, S. Sasikala, and S. Murugan, “Raspberry pi-enabled wearable sensors for personal health tracking and analysis,” in *International Conference on Self Sustainable Artificial Intelligence Systems, ICSSAS 2023 - Proceedings*, Oct. 2023, pp. 1254–1259, doi: 10.1109/ICSSAS57918.2023.10331909.

[2] R. Raman, V. Sujatha, C. Bhupeshbhai Thacker, K. Bikram, M. B Sahaai, and S. Murugan, “Intelligent parking management systems using IoT and machine learning techniques for real-time space availability estimation,” in *International Conference on Sustainable Communication Networks and Application, ICSCNA 2023 - Proceedings*, Nov. 2023, pp. 286–291, doi: 10.1109/ICSCNA58489.2023.10370636.

[3] A. Deepa, R. Latha, T. S. Kumar, N. K. Manikandan, J. Preetha, and S. Murugan, “IoT-based wearable devices for personal safety and accident prevention systems,” in *2023 2nd International Conference on Smart Technologies for Smart Nation, SmartTechCon 2023*, Aug. 2023, pp. 1510–1514, doi: 10.1109/SmartTechCon57526.2023.10391691.

[4] B. Meenakshi, B. Gopi, L. Ramalingam, A. Vanathi, S. Sangeetha, and S. Murugan, “Wireless sensor networks for disaster management and emergency response using SVM classifier,” in *2023 2nd International Conference on Smart Technologies for Smart Nation, SmartTechCon 2023*, Aug. 2023, pp. 647–651, doi: 10.1109/SmartTechCon57526.2023.10391435.

[5] M. Senthil Kumar, H. Azath, A. K. Velmurugan, K. Padmanaban, and M. Subbiah, “Prediction of alzheimer’s disease using hybrid machine learning technique,” in *AIP Conference Proceedings*, 2023, vol. 2523, doi: 10.1063/5.0110283.

[6] B. M. Pavlyshenko, “Machine-learning models for sales time series forecasting,” *Data*, vol. 4, no. 1, p. 15, Jan. 2019, doi: 10.3390/data4010015.

[7] Y. Niu, “Walmart sales forecasting using XGBoost algorithm and feature engineering,” in *Proceedings - 2020 International Conference on Big Data and Artificial Intelligence and Software Engineering, ICBASE 2020*, Oct. 2020, pp. 458–461, doi: 10.1109/ICBASE51474.2020.00103.

[8] M. Li, S. Ji, and G. Liu, "Forecasting of Chinese e-commerce sales: an empirical comparison of ARIMA, nonlinear autoregressive neural network, and a combined ARIMA-NARNN model," *Mathematical Problems in Engineering*, vol. 2018, pp. 1–12, Nov. 2018, doi: 10.1155/2018/6924960.

[9] M. Bohanec, M. Kljajić Borštnar, and M. Robnik-Šikonja, "Explaining machine learning models in sales predictions," *Expert Systems with Applications*, vol. 71, pp. 416–428, Apr. 2017, doi: 10.1016/j.eswa.2016.11.010.

[10] M. Mohammed, M. B. Khan, and E. B. M. Bashier, *Machine learning: algorithms and applications*. CRC Press, 2017.

[11] D. Rasadurai and M. Raguraman, "Analyzing effectiveness of service quality in Tirupattur post office toward postal life insurance (PLI) and rural postal life insurance (RPLI)," *International Journal of Financial Engineering*, vol. 10, no. 01, Nov. 2023, doi: 10.1142/s242478632250030x.

[12] K. Singh, P. M. Booma, and U. Eaganathan, "E-commerce system for sale prediction using machine learning technique," *Journal of Physics: Conference Series*, vol. 1712, no. 1, p. 12042, Dec. 2020, doi: 10.1088/1742-6596/1712/1/012042.

[13] M. J. Kane, N. Price, M. Scotch, and P. Rabinowitz, "Comparison of ARIMA and random forest time series models for prediction of avian influenza H5N1 outbreaks," *BMC Bioinformatics*, vol. 15, no. 1, Aug. 2014, doi: 10.1186/1471-2105-15-276.

[14] X. Qiu, L. Zhang, P. Nagaratnam Suganthan, and G. A. J. Amaratunga, "Oblique random forest ensemble via least square estimation for time series forecasting," *Information Sciences*, vol. 420, pp. 249–262, Dec. 2017, doi: 10.1016/j.ins.2017.08.060.

[15] H. Chen and H. A. Rakha, "Real-time travel time prediction using particle filtering with a non-explicit state-transition model," *Transportation Research Part C: Emerging Technologies*, vol. 43, pp. 112–126, Jun. 2014, doi: 10.1016/j.trc.2014.02.008.

[16] N. Chandru and M. N. Devi, "Financial services and benefits of investing in post office savings schemes," *International Journal for Modern Trends in Science and Technology (IJMTST)*, vol. 9, no. 8, pp. 81–88, 2023.

[17] K. R. Reshma and V. Shacheendran, "Antecedents of customer satisfaction in postal financial services: an investigation in India post," *SDMIMD Journal of Management*, pp. 1–14, Mar. 2024, doi: 10.18311/sdmimd/2024/33322.

[18] Y. Y. Jiang, "Conscription insurance in pre-war Japan - Private enterprise and national interest," *Contemporary Japan*, vol. 36, no. 1, pp. 103–125, Oct. 2024, doi: 10.1080/18692729.2022.2133667.

[19] D. L. Pandey, N. Risal, B. J. Basnet, and R. Sigdel, "Factors influence on customers' satisfaction in government owned life insurance firm: a case of rastriya beema sansthan, Nepal," *Asian Journal of Economics, Business and Accounting*, vol. 24, no. 2, pp. 166–172, Jan. 2024, doi: 10.9734/ajeba/2024/v24i21232.

[20] M. Carannante, V. D'amato, S. Haberman, and M. Menzietti, "Frailty-based mortality models and reserving for longevity risk," *Geneva Papers on Risk and Insurance: Issues and Practice*, vol. 49, no. 2, pp. 320–339, Apr. 2024, doi: 10.1057/s41288-024-00319-y.

[21] M N Vidyalaxmi and N. Kayarkatte, "Literature review on determinants of investment choice in indian post office schemes," *EPRA International Journal of Multidisciplinary Research (IJMR)*, pp. 121–126, Jan. 2024, doi: 10.36713/epra15417.

[22] S. M. Vadivel and K. Boobalan, "Influences of Indian postal service quality factors on customer satisfaction amidst Covid-19 pandemic: an empirical study," *International Journal of System Assurance Engineering and Management*, vol. 15, no. 2, pp. 758–773, Jun. 2024, doi: 10.1007/s13198-023-01949-6.

[23] A. van der Heide and S. Kohl, "Private insurance, public welfare, and financial markets: alpine and maritime countries in comparative-historical perspective," *Politics and Society*, vol. 52, no. 2, pp. 268–303, Mar. 2024, doi: 10.1177/00323292231161445.

[24] F. Zuiderveen Borgesius, P. Hacker, N. Baranowska, and A. Fabris, "Non-discrimination law in Europe, a primer. Introducing European non-discrimination law to non-lawyers," *SSRN Electronic Journal*, 2024, doi: 10.2139/ssrn.4786956.

[25] S. Rajalakshmi and S. Selvakumar, "Impact of trust factors on customer satisfaction in speed post service in Chennai: explanatory sequential mixed methods study," *Educational Administration: Theory and Practice*, vol. 30, no. 4, pp. 7699–7710, 2024.

[26] P. Tanuseputro *et al.*, "Palliative end-of-life medication prescribing rates in long-term care: a retrospective cohort study," *Journal of the American Medical Directors Association*, vol. 25, no. 3, pp. 532-538.e8, Mar. 2024, doi: 10.1016/j.jamda.2023.11.026.

[27] P. Purwanto, M. Doing, and R. Riduwan, "Understanding the issues of failure to pay life insurance claims: A perspective on absolute responsibility at PT. Jiwasraya," *Journal of Law Science*, vol. 6, no. 1, pp. 70-80, 2024.

[28] M. Agnes, R. H. Koestoer, and A. Sodri, "Social and environmental risks integration into underwriting of non-life insurance: a review of sustainable finance in Indonesia," *Jurnal Ilmu Lingkungan*, vol. 21, no. 1, pp. 125–131, Dec. 2023, doi: 10.14710/jil.21.1.125-131.

[29] J. Puluhulawa, M. H. Muhtar, M. Towadi, V. Swarianata, and Apripari, "The concept of cyber insurance as a loss guarantee on data protection hacking in Indonesia," *Revista de Direito, Estado e Telecomunicacoes*, vol. 15, no. 2, pp. 132–145, Sep. 2023, doi: 10.26512/lstr.v15i2.44206.

[30] M. I. Al-Banna Ismail, A. T. Bon, Sukono, A. R. Effendie, and J. Saputra, "Investigating the collective value at risk model (CVaR) and its application on real data for life insurance," *Decision Science Letters*, vol. 12, no. 2, pp. 399–406, 2023, doi: 10.5267/j.dsl.2022.12.004.

BIOGRAPHIES OF AUTHORS

Mr. Thangavelu Ananadaraj Rajasekaran is currently deputed as a technical analyst at the Indian Postal Payment Bank, Chennai. In his capacity, he handles the report framework in Oracle 12g, contributing to the development, analysis, and optimization of various reporting solutions. He also serves as an LSG Postal Assistant at the Department of Posts, Park Town, Chennai, where he actively supports various technical and operational aspects. In addition to his Ph.D. pursuits, he holds a postgraduate degree in Electronics and Communication Engineering (ECE) from Anna University, Guindy, a prestigious institution known for producing world-class engineers and technologists. He is deeply passionate about artificial intelligence (AI), machine learning (ML), data science, and big data handling, continuously expanding his knowledge in these research fields and contributing to innovative solutions in these fields. He can be contacted at email: tarajasekaran@indiapost.gov.in.

Dr. Pichamuthu Vijayalakshmi is presently working as an associate professor in the Department of Electronics and Communication Engineering, Vels Institute of Science, Technology and Advanced Studies (VISTAS) Chennai. She completed B. Tech Instrumentation from Madras Institute of Technology, Anna University and M.E Applied Electronics from Anna University, Chennai, India. She was awarded Ph.D. degree in the year 2020 for her outstanding research contribution in the field of Underwater Communication and Machine learning applications. She has 17 years of rich experience in teaching and research. Her area of interest includes underwater communication sensor networks and system design with machine learning and data science. She has supervised more than 30 UG and PG scholars and 6 Ph.D. Scholars. She has authored 4 books and published more than 30 papers in Scopus and other indexed journals. She has also published patents and received grants. She is fellow in IETE with life time member and has professional membership in ISOI, InRes and received InRes-Academic Excellence Award 2022 and Faculty Excellence awards from VISTAS. She also contributed in extension activities and service through NSS as a programme officer. He can be contacted at email: viji.se@velsuniv.ac.in.

Dr. Velayutham Rajendran completed his M. Tech degree in physical engineering from the Indian Institute of Science, Bangalore, India, in 1979. In 1993, he received Ph.D. degree in Electrical and Electronics Engineering from Chiba University, JAPAN. He has more than 35 years' experience in Academic and Research Experience. He has been with National Institute of Ocean Technology, Chennai, India, as a Project Director and Head (Marine Instrumentation and Ocean Acoustics and Ocean Observation Systems). He is currently working as professor and director, in Department of ECE. His research interests include underwater wireless sensor network, cognitive radio and software defined radio communication, HF radar, tsunami warning system and underwater noise measurement systems. He is a life fellow of Ultrasonic Society of India, India (USI), January 2001, Associate Member of Acoustical Society of America, USA, January 2010, Member of IEEE, USA, January 2010, Life fellow of Institution of Electronics and Telecommunication Engineering (IETE), India, January 2012. He was elected twice as Vice Chairman- Asia Execution Board of Data Buoy Co-operation Panel (DBCP) of Intergovernmental Oceanographic Commission (IOC) / World Meteorological Organization (WMO) of UNSCO, in October 2008. and September 2009. He can be contacted at email: director.ece@velsuniv.ac.in.