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Telco Customer Churn Prediction Using ML Models

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Abstract: This study aims to develop a robust customer churn prediction model in the communications industry. Using various machine learning and analysis methods, we aim to improve the accuracy and efficiency of customer churn prediction. Our research explores integration techniques such as bundling and bracing to combine predictions from multiple models and reduce variability. We likewise lead awareness examination to assess the effect of various factors on the presentation model. We calibrate the model through factors like learning rate, number of layers, and group size and decide the best arrangement to assess the misfortune. We likewise broaden the existing examination of client rivalry forecasts in the correspondence business by consolidating the utilization of vast amounts of information. By utilizing the force of extensive information examination, we expect to build the versatility and effectiveness of client-agitate forecast models. Analysis of this study's consequences included using different AI calculations. The fundamental reason for this study is to anticipate client beat in the correspondence business utilizing AI and extensive information. Research has shown that client agitates can be precisely expected using this procedure.

Keywords: *Artificial Neural Network, Customer, Churn, Machine Learning, Predictive Models, Telecommunications*

1. Introduction

In a severe and quickly evolving business, it is critical to foresee a client beat or stir (the probability that a client will quit working). Its significance comes from the binding monetary effect of client beat, making it a wellspring of worry in numerous enterprises. Adverse consequences include correspondence, business, protection, and less apparent products like betting. These organizations find solace in coordinating information science and AI methods by utilizing the force of prescient models. The power of huge amounts of information, combined with AI's high-level calculations, brings prevalent client-beat investigation abilities, permitting organizations to proactively foresee and forestall client agitation. Furthermore, the café and travel industry understand AI's capability to comprehend client inclinations and increment brand reliability. By utilizing colossal information, prescient examination, and artificial reasoning, organizations in these enterprises have the chance to acquire better experiences in client commitment and cost commitment. AI models have been demonstrated to be significant devices for monetary foundations—phase of the client lifecycle.

From responsive models to cutthroat deals and serious offers, these models investigate organized information like past clients and credit reimbursements to pursue informed choices. This permits monetary organizations to foresee business development, evaluate moneylenders' dissolvability, and further develop the advanced endorsement process. In correspondence, client agitate expectation has become progressively significant for organizations hoping to decrease stir rates and hold clients. AI strategies have been demonstrated to be extremely helpful in this field. Overwhelmingly of information created by correspondence organizations, AI calculations can recognize examples and signs that demonstrate potential client beat.

One way to get momentum is to fill in as an interpersonal organization. This approach includes breaking down the connection between clients in the organization to distinguish persuasive individuals who can impact the way of others. By coordinating these assets into prescient models, Telcos can more readily figure out changes in client conduct and make vital field-tested strategies to decrease agitation. One more effective method for anticipating is to utilize backing and arbitrary woods models. Lu et al. showed that Supporting is successful in foreseeing client associations in business correspondences. This technique uses joint figuring out how to consolidate numerous frail students into

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a solid model, subsequently working on the exactness of the forecast. Then again, Ullah et al. proposed using an Irregular Woods model, which uses the force of choice trees to foresee and decrease client stir proficiently.

Prominently, client stir forecast isn't restricted to the media communications industry alone. It has tracked down applications in different areas, including banking, protection, and cell phone organizations. The capacity to precisely anticipate client beats is also critical in these enterprises, as it permits organizations to address issues and hold their important clients proactively. In recent years, there has been interest in using data analytics and machine learning algorithms for customer churn prediction in the communications industry. Researchers have explored various methods, including neural networks, decision trees, Bayesian networks, and genetic algorithms. However, there needs to be research in the literature on combining genetic algorithms and neural networks for customer churn prediction on social media.

1.1. Abbreviations and Acronyms

- Telcos: Telecommunications Companies
- Lu et al.: Refers to a specific set of authors in a scholarly context (every day in academic writing).
- Ullah et al.: Similar to the above, they refer to another set of authors in a scholarly context.
- DNA: Decision Trees and Random Forests (in the context of churn prediction models)

2. Literature Review

Consumer communication refers to the phenomenon where consumers decide to switch mobile service providers [1]. Considering the intense competition in the telecommunications industry, predicting customer competition is essential for telecom operators to retain existing customers and improve overall business [2]. Many studies have been done to solve the challenge of using machine learning models for customer interaction [3]. Such studies use machine learning techniques to model two paths of customer behavior: abandonment (leaving the service) or non-abandonment. Light [4]. Predicting customer churn is similar to solving the binary classification problem, where customers are classified according to their likelihood of leaving or continuing to use the service [5].

Attrition generally falls into two categories: voluntary and involuntary. Voluntary churn refers to the customer's decision to change providers, while involuntary churn refers to events beyond the customer's control, such as relocation or service [6]. Many studies focus specifically on voluntary decision-making due to its direct impact on the financial importance of telecommunication companies. Machine learning models for customer prediction have been widely studied in many industries, including banking, insurance, Internet service providers, and especially business communications [7]. In the telecommunications industry, accurately predicting customer churn is crucial for telecom operators to develop retention strategies and reduce revenue. Various types of machine learning have been used for user interaction, including logistic regression, support vector machine, decision tree, and random forest model [8].

These models were chosen because they can work well on large data sets with many different concepts and allow for various customer-related characteristics and behaviors to be taken into the predictive model [9]. Additionally, recent advances in data analysis and machine learning algorithms have improved the accuracy and performance of radio churn prediction models [10].

These models utilize historical customer data such as call records, billing information, customer demographics, and service usage patterns to identify patterns and trends indicative of customer churn[11]. By employing machine learning algorithms such as Deep Learning, Logistic Regression, and Na√Øve Bayes, telco operators can analyze these patterns and accurately predict which customers are at a higher risk of churning [12].

The client, on the other hand, has applications past the interchange business. Different enterprises, for example, banking, protection, and betting, likewise benefit from shopper betting [13]. These organizations can utilize AI innovation to investigate client conduct and recognize potential client stirs, permitting them to utilize designated measurements to protect client esteem [13]. Utilizing AI models to agitate expectations is significant for advertising interchanges and different organizations. It permits organizations to figure out client conduct, foresee client beat, and foster methodologies to hold clients and lessen low income. [3] The writing survey shows that AI models for pre-client matching are broadly utilized across businesses, including advertising correspondences. This model has been demonstrated to function admirably in circumstances where media communications information is thick and sought after, giving more unsurprising outcomes. The prescient properties of these AI models can be extremely useful in creating techniques against buyer extortion [14]. Organizations can utilize these forecasts to make customized designs and give the right impetuses and worth to fabricate client commitment and maintenance [15].

Predictive models have great potential to help develop customer-centric businesses in the future [16]. They help meet customer needs and preferences, which is vital in improving the overall customer experience [17]. Businesses can reduce customer churn by improving customer experience and carefully measuring satisfaction, thus increasing revenue [18]. Although these models are widely used in many fields, continued machine learning and data analysis advances should provide customers with more competitive forecasting capabilities.

Social influence on consumer behavior gives us other benefits for gambling [20]. By analyzing customer interactions and understanding current competitor relationships, companies can adjust their forecast models and thus actually improve their forecasts [21]. This analysis can reveal consumer behavior patterns and provide insight into which factors play the most crucial role in consumer competition [2][22].

Jahromi et al. demonstrated the success of customer matching prediction in the B2B environment, demonstrating the effectiveness of this approach and its potential in different fields [23]. Identifying future crisis-prone customers allows businesses to take proactive measures to help maintain customer loyalty and retention [24]. Using machine learning models is similar to predicting customer churn in financial markets [3] [25]. Amid the rapid growth of mobile internet, banks have capitalized on the potential of machine learning to analyze massive customer log data, identifying temporal patterns and trends in customer behavior [25][18]. This helps banks forecast which customers are likely to churn potential to be applied in various industries. This, coupled with ongoing research and improvements in predicting churn, allows companies to employ even more precise and effective retention strategies [11][26].

The following findings demonstrate the benefits of using churn prediction models: Sending churn messages to prevent customers who are likely to churn can increase profitability [27][26]. This approach is financially savvy because the expense of holding a current client differs from that of securing another client. It likewise features the significance of creating precise stir forecast models [11] [28]. Indeed, even a slight expense improvement because of exact determining can expand an organization's productivity [7] [29].

These investigations provide solid groundwork for utilizing algorithmic techniques to foresee and tackle client stir issues [30]. As information science and AI keep on propelling, these methods offer a superior method for foreseeing client rivalry across various ventures, including interchanges, promoting tensions, and protection [3]. They make significant data that empowers organizations to connect with clients and lessen client contest [26] [31].

Likewise, in an industry with a high misfortune rate, for example, the betting business, the nature of client experience is vital [31]. The expectation model not only assists with assessing the likelihood of a client exit from the market but also assists with understanding the main drivers of client rivalry [31]. Subsequently, organizations can formulate techniques to recognize these issues, further developing client maintenance and business performance.[32].

3. Proposed Model

In our quest for viable AI calculations for foreseeing client stirs, we will investigate a scope of strategies. These incorporate calculated relapse, choice trees, Backing Vector Machines, counterfeit brain organizations, and Bayesian classifiers. The complete flowchart of the proposed model is shown in Fig. 1. These strategies have demonstrated their adequacy regarding client beat expectations.

Whenever we've prepared these models, the following stage is to survey their presentation utilizing different measurements, including exactness, accuracy, review, and the F1 score. This assessment cycle will empower us to think about the adequacy of every calculation and, at last, select the one that performs best.

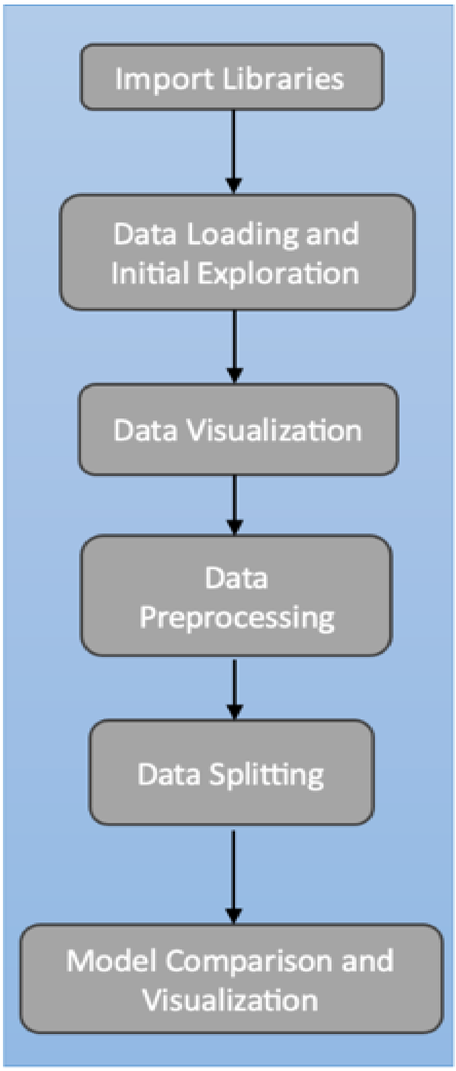

Fig. 1. Proposed model

Besides, we will dive into the investigation of element significance. This involves inspecting what various elements mean for the exactness of our expectations. By evaluating the meaning of each element, we can decide if it impacts foreseeing client stir. This examination is significant in assisting us with acquiring a more profound comprehension of the variables at play in our prescient model. This will help us with understanding the critical drivers of client stir and permit telcos to find proactive ways to hold clients.

To help our prescient model, we fostered a product application that utilizes a numerical model given calculated relapse examination. The application will permit telephone organizations to take advantage of the arbitrariness of clients and foresee their probabilities. Organizations can utilize this product to pursue informed choices and dispense assets to increment consumer loyalty and lessen client beat.

These exploration discoveries hold extraordinary commitment for cell phone organizations, offering them significant bits of knowledge for asset the executives and the execution of designated systems to improve the client experience. By working on our capacity to foresee client stirs, broadcast communications organizations (telcos) can settle on additional educated choices regarding asset assignment and vital preparation, at last prompting further developed client maintenance.

An essential move toward our examination includes highlight choice. This cycle involves recognizing the factors that altogether impact stir forecast, consequently improving the precision and general execution of our model. This engages telcos to zero in on the main thing most to their clients.

Moreover, we carefully examine various AI calculations to figure out which succeeds in foreseeing beat. This relative examination reveals insight into the qualities and shortcomings of every measure, empowering telcos to settle on informed conclusions about which one to integrate into their expectation models.

Notwithstanding calculation determination, we devise a strategy to assess the viability of our proposed stir expectation model. This involves dividing the information into preparing and testing sets, with a resulting assessment of the model's exactness, accuracy, review, and F1 score. We additionally utilize cross-approval methods, for example, k-crease cross-approval, to reinforce the adequacy of our intuitive expectation model. This approach permits us to extensively survey the model's prescient abilities across various subsets of information, upgrading its heartiness.

To upgrade the exactness and dependability of our stir expectation model, we dig into highlight designing. This includes changing and forming new highlights in light of existing information, utilizing space information, and aptitude to separate significant data that can reinforce our model's presentation.

Our examination reaches out past only foreseeing client agitate; we try to grasp the hidden drivers of stir. We break down client correspondence information to recognize essential qualities that add to the client's steady loss. This cycle includes inside and out information research and factual investigation to divulge examples and connections among elements and client stir.

Furthermore, we dig into the domain of AI's job in client stir expectations. Drawing from examining specialists like Mama, Xia, and Vafeiadis, we think about the presentation of different AI strategies in anticipating beats inside the correspondence business [12]. By integrating their discoveries and systems, we mean propelling our exploration and adjusting our practices to laid-out experiences.

Whenever we've fostered a powerful prescient model and recognized the elements impacting client stir, we influence calculated relapse examination procedures to make a numerical model. This approach supports measuring and understanding the many factors of foreseeing client stir. Strategic relapse is a double circulation factual technique usually used to foresee whether somebody will separate.

Our examination will include preparing a strategic relapse model utilizing the telephone client dataset, which involves the pertinent elements recognized through our investigation. With calculated relapse, we can foresee the likelihood of a client beating in light of different factors. This prescient capacity offers a significant comprehension of the possible results of client steady loss, empowering telcos to go to proactive lengths to hold these clients and relieve the gamble of stir.

Even with the strategic relapse model, we intend to foster a product application that uses this model to help our exploration. This application will furnish telephone organizations with admittance to client information and deal forecasts regarding the probability of client stir. By using these prescient apparatuses, telcos can successfully focus on and tailor their maintenance techniques, guaranteeing that assets are apportioned in the most proficient and savvy way.

Besides, our exploration reaches out past calculated relapse models. We will investigate other AI calculations, for example, choice tree surmising and support vector machines, which have been broadly utilized in shopper stir expectation inside the broadcast communications industry. By looking at the presentation of different calculations in our exploration, we mean to acquire a more profound comprehension of which measures are ideal for stirring expectations inside our particular setting.

Also, we will tackle the force of outfit and half-and-half models in our exploration. These models join the qualities of different calculations to upgrade prescient exactness and power. By incorporating other AI procedures, including choice trees, fake brain organizations, and backing vector machines, we can gain from their singular assets and make up for their shortcomings. This approach permits us to make a more extensive and prescient solid structure. The models utilized are:

Random Forest Classifier: Outfit technique in light of choice trees. Reasonable for arranging errands. It Lessens overfitting and increments precision through stowing and element choice [33]. Gradient Boosting Classifier: Gathering strategy that forms choice trees consecutively. Likewise, it is utilized for grouping errands. Joins the results of different feeble students to make significant areas of strength for a model [34].

Linear Regression: Utilized for demonstrating straight connections between factors. Appropriate for relapse errands. It fits a straight line (hyperplane) to limit the number of squared blunders [35]. Polynomial Regression: Stretches out direct relapse to catch nonlinear connections. Reasonable for relapse assignments. It fits polynomial capabilities to the information, which can deal with additional complicated links [36]. Logistic Regression: Utilized for double arrangement assignments. Models the likelihood of a perception having a place with a particular class. It uses the strategic capability (Sigmoid) to plan input highlights to a likelihood range somewhere between 0 and 1 [37].

Support Vector Regression (SVR): Utilized for relapse errands, especially with non-straight connections. Distinguishes a hyperplane that best fits the information while limiting the safety buffer. Can be reached with various portion capabilities to deal with different information designs [38]. Artificial Neural Network (ANN): Flexible AI model enlivened by natural brain organizations. Appropriate for both relapse and order undertakings. It comprises layers of interconnected neurons that can catch mind-boggling and nonlinear connections in information [39].

4. Result Analysis

After reviewing the outcomes of the diverse studies mentioned earlier, it becomes evident that machine learning algorithms exhibit significant potential in forecasting customer churn within the telecommunications industry, mainly when employed on extensive datasets. One key revelation is that customer attrition is impacted by many factors, encompassing customer satisfaction, call quality, brand perception, and individual characteristics. These variables play a pivotal role in influencing whether a customer decides to terminate their subscription or switch to an alternative service provider.

By considering these multifaceted elements, mobile operators gain a deeper insight into the underlying principles governing customer churn. This heightened understanding empowers them to formulate and implement effective strategies for customer retention. In essence, this research demonstrates how leveraging the power of data-driven insights and machine learning can be a game-changer in the telecommunications sector, ultimately fostering improved customer relations and business sustainability.

To enhance the precision of customer churn prediction models within the communications industry, researchers have explored a fascinating blend of customer and product mixes by employing genetic algorithms and neural networks. While past investigations have predominantly examined the effectiveness of genetic algorithms and neural networks separately, the fusion of both methods has remained relatively uncharted territory. It's important that this blend, especially in the domain of foreseeing client weakening in the broadcast communications industry, has yet to get far-reaching consideration. Despite the presence of individual examinations on the utilization of hereditary calculations and brain organizations, the synergistic capability of their joined application in gauging client agitate presently can't be completely saddled. Thus, it offers an intriguing and open door for additional examination and investigation to uncover this inventive methodology's expected benefits and viability.

Past AI strategies in the field of client beat identification in the broadcast communications area have likewise dug into the domain of information mining techniques. Scientists have taken advantage of a different cluster of instruments, including factual procedures, design acknowledgment, artificial reasoning, and other calculations, to investigate and remove significant bits of knowledge from the immense and unpredictable datasets available to them. This thorough methodology, which goes past conventional AI, considers a more comprehensive assessment of variables impacting client whittling down, opening up new roads for understanding and further developing client maintenance procedures.

A. Details about MAE, MSE, and R2 metrics:

Mean Absolute Error (MAE): MAE is an essential and instinctive measurement for estimating the typical outright contrast between anticipated and natural qualities. It is determined as the mean of the outright differences between each expected worth ($\hat{y}_i$) and the comparing genuine price (y_i):

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

MAE is communicated in similar units as the objective variable, making it simple to decipher. It gives a proportion of the typical extent of mistakes in the expectations. MAE provides an equivalent load for all blunders, implying it is less delicate to anomalies than MSE [40]. Mean Squared

Error (MSE): MSE is a metric that computes the normal of the squared contrasts between anticipated and genuine qualities. It is determined as the mean of the squared differences between each expected worth ($\hat{y}_i$) and the related actual worth (y_i):

$$MSE = \frac{1}{n}\sum_{i=1}^{n} (y_i - \hat{y}_i)^2$$

Squaring the blunders in MSE gives more weight to more significant mistakes, making it delicate to anomalies. MSE is communicated in squared units, which may not be as natural as MAE. It's regularly utilized when you must punish more enormous blunders than modest ones [40].

R-squared (R^2): R^2, otherwise called the coefficient of assurance, is a metric that determines the extent of the change in the reliant variable (the objective) that is made sense of by the free factors (the elements) in a relapse model. R^2 values range from 0 to 1, with 1 showing an ideal fit and 0 demonstrating that the model doesn't make sense of any changes in the information. R^2 is $R^2 = 1 - (SSE/SST)$, where SSE is the number of squared mistakes (equivalent to in MSE), and SST is the absolute number of squares, which estimates the all-out change in the objective variable. An R^2 esteem near 1 shows a decent model fit, while values near 0 recommend that the model doesn't make sense of a significant part of the change in the information [41], as shown in Fig 2 and 3.

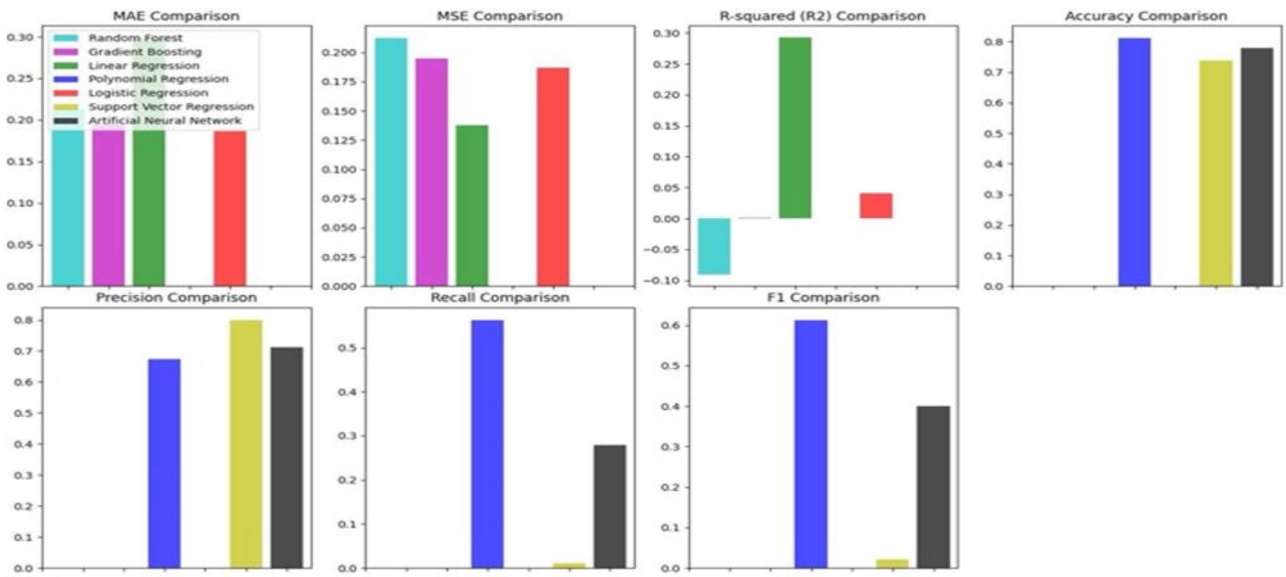

Fig 2: Comparison of all metrics of all models

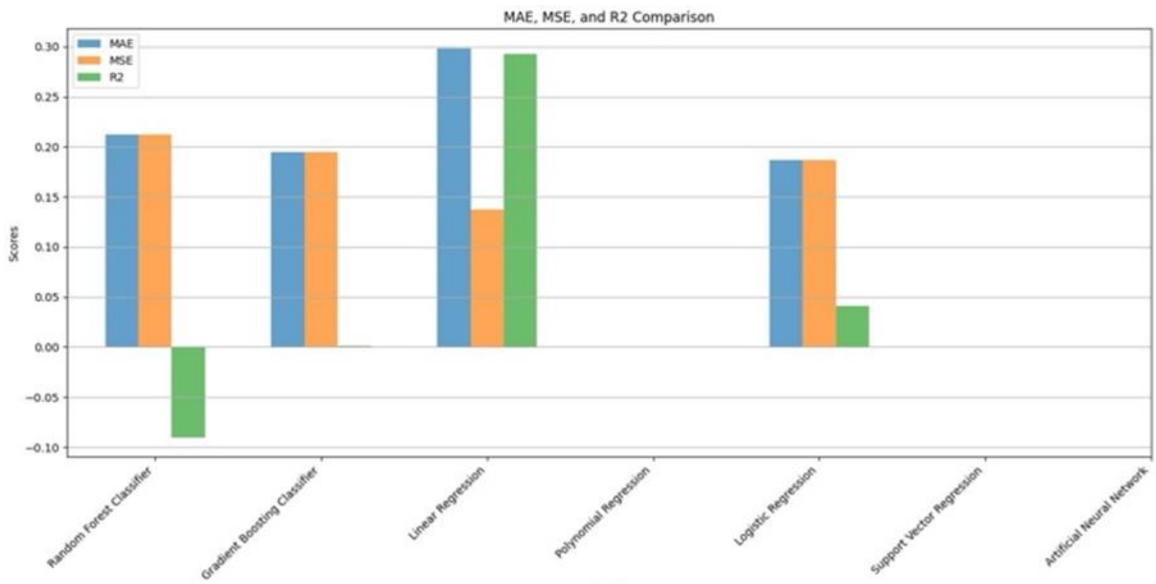

Fig 3: Comparison of all models' MAE, MSE, and R^2 metrics.

B. Details about accuracy, precision, recall, and F1:

Accuracy: Accuracy estimates the precision of optimistic forecasts made by the model. It centers around the extent of genuine positive expectations compared with all occasions anticipated as confident. It is determined as Accuracy = TP/(TP + FP). Accuracy is especially significant when bogus up-sides are exorbitant or unfortunate. It lets you know how well the model performs when it predicts a positive result [42].

Precision: Precision for the most precise measurement is entirely possible and measures the general rightness of the model's forecasts. It is determined as the proportion of accurately anticipated examples to the absolute number of cases: Exactness = (TP + TN)/(TP + TN + FP + FN). TP (Genuine Up-sides) is the quantity of accurately anticipated positive examples, TN (Genuine Negatives) is the quantity of accurately predicted adverse occasions, FP (Misleading Up-sides) is the number of negative cases expected as inevitable, and FN (Bogus Negatives) are the number of positive occurrences anticipated as unfavorable. While precision gives an essential proportion of rightness, by and large, it may not be reasonable for imbalanced datasets, where one class overwhelms the other [43].

Recall (Sensitivity or True Positive Rate): Recall estimates the model's capacity to distinguish all significant cases inside the positive class. It centers around the extent of genuine optimistic forecasts compared with all actual occurrences. It is determined as Review = TP/(TP + FN). Review is significant when it is exorbitant or unfortunate to miss joyous occasions. It lets you know how well the model distinguishes genuine positive cases [44].

F1 Score: The F1 score is a symphonious means of accuracy and review, giving a reasonable proportion of a model's exhibition. It is determined as: F1 = 2 * (Accuracy * Review)/(Accuracy + Review). The F1 score adjusts accuracy and review, making it a helpful metric when you want a solitary worth to assess model execution. It is beneficial when there is a lopsided class conveyance [45], as shown in Fig 4.

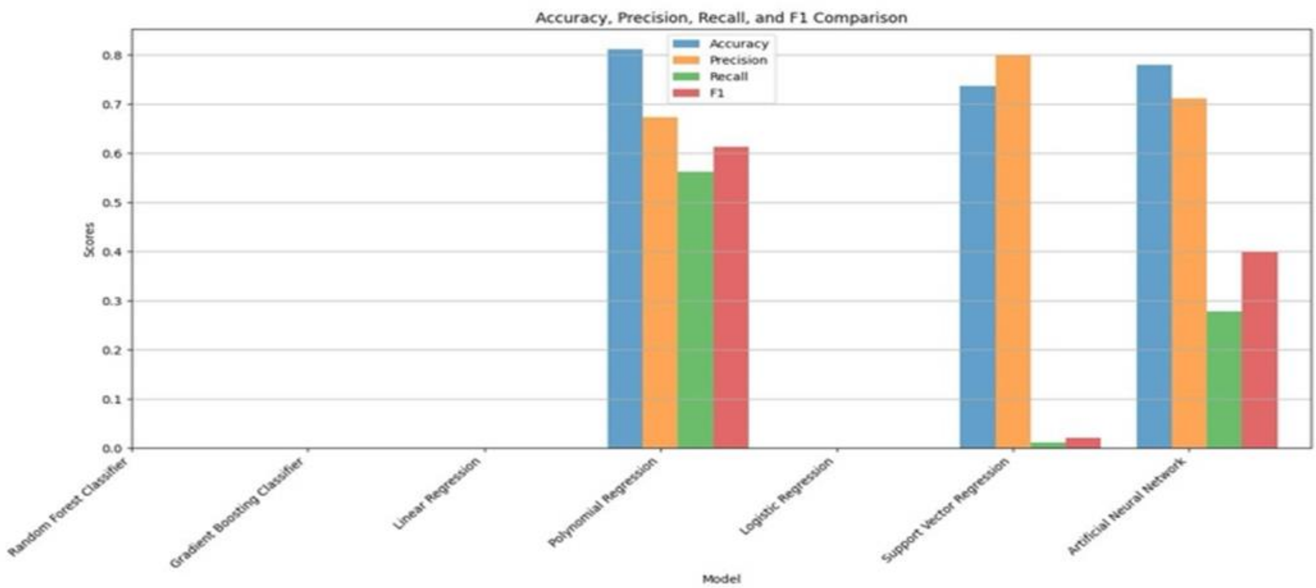

Fig 4. Comparison of accuracy, precision, recall, and F1 comparison.

5. Conclusion

In summary, our extensive literature review underscores the substantial potential of machine learning techniques for predicting customer churn within the telecommunications industry. The research we've examined demonstrates the immense value of harnessing sophisticated algorithms, such as logistic regression, decision trees, neural networks, support vector machines, and ensemble methods, to analyze complex, multivariate customer datasets. These advanced models enable telecom companies to uncover subtle predictive patterns and trends that serve as early warning signs of customer churn. By employing machine learning to scrutinize various parameters, including usage behaviors, service perceptions, demographics, social connections, and service histories, telcos can attain a multifaceted understanding of the factors influencing churn. Moreover, techniques like deep learning and natural language processing allow for including unstructured data, such as customer communications, offering even more nuanced insights. The predictive capabilities of these machine learning models empower telecom companies to proactively identify potential churners, enabling them to direct their retention marketing efforts and incentives toward high-risk customers, ultimately enhancing customer lifetime value. Even slight improvements in retention, driven by accurate predictions, can translate into substantial profitability gains, underscoring the critical importance of maximizing predictive performance. While considerable research has been dedicated to individual algorithms like logistic regression, SVM, and neural networks, our review reveals that the combination of genetic algorithms and neural networks still needs to be explored in telecom churn prediction. This presents a unique opportunity for hybrid models to enhance prediction accuracy. Our proposal aims to tackle this challenge by rigorously comparing various algorithms using real-world telecommunications data. Furthermore, incorporating big data analytics can significantly enhance the scalability and efficiency of using big data churn prediction models within the telecommunications sector. Our solution is rooted in existing data and seeks to push the boundaries of machine learning-based predictions. The insights generated are intended to offer practical advice and research-backed recommendations that telcos can implement to enhance their forecasting processes, ultimately leading to increased customer retention, enhanced customer lifetime value, and improved profitability in a fiercely competitive market.

References

[1] Anindito De "Telecom Revenue Enhancement and Churn Prevention - Wipro," wipro.com, (Accessed 28 Oct. 2023).

[2] Geetha, S. & Kaliappan, Vishnu. (2018). Tweet Analysis Based on Distinct Opinions of Social Media Users. 1-6. 10.1109/ICSNS.2018.8573619.

[3] Sun, Yuechi & Liu, Haiyan & Gao, Yu. (2023). Research on customer lifetime value based on machine learning algorithms and customer relationship management analysis model. Heliyon. 9. e13384. 10.1016/j.heliyon.2023.e13384.

[4] Peng, Ke & Peng, Yan. (2022). Research on Telecom Customer Churn Prediction Based on GA-XGBoost and SHAP. Journal of Computer and Communications. 10. 107-120.10.4236/jcc.2022.1011008.

[5] Sana, Joydeb & Abedin, M. & Rahman, Mohammad & Rahman, Mohammad. (2022). Using data transformation methods and feature selection, a novel customer churn prediction model for the telecommunication industry. PLOS ONE.17.e0278095.10.1371/journal.pone.0278095.

[6] Börühan, G. (2022). Churn Customer Management in Retail Industry: A Case Study. İzmir İktisat Dergisi , 37 (4) , 1094-1118 . DOI: 10.24988/ije.1070830

[7] hen, Hao & Tang, Qian & Wei, Yifei & Song, Mei. (2021). Churn Prediction Model of Telecom Users Based on XGBoost. Journal on Artificial Intelligence. 3. 115-121. 10.32604/jai.2021.026851.

[8] Hou, Hongwei & Tang, Kunzhi & Liu, Xiaoqian & Zhou, Yue. (2022). Application of Artificial Intelligence Technology Optimized by Deep Learning to Rural Financial Development and Rural Governance. Journal of Global Information Management. 30. 1-23. 10.4018/JGIM.289220.

[9] Fareniuk, Yana & Zatonatska, Tetiana & Dluhopolskyi, Oleksandr & Kovalenko, Oksana. (2022). Customer Churn Prediction Model: A Case of the Telecommunication Market. ECONOMICS. 10. 10.2478/eoik-2022-0021.

[10] Nalatissifa, Hiya & Pardede, Hilman. (2021). Customer Decision Prediction Using Deep Neural Network on Telco Customer Churn Data. Jurnal Elektronika dan Telekomunikasi. 21. 122. 10.14203/jet.v21.122-127.

[11] Kostić, Stefan & Simic, Mirjana & Kostić, Miroljub. (2020). Social Network Analysis and Churn Prediction in Telecommunications Using Graph Theory. Entropy. 22. 753. 10.3390/e22070753.

[12] Suh, Youngjung. (2023). Machine learning-based customer churn prediction in-home appliance rental business. Journal of Big Data. 10. 10.1186/s40537-023-00721-8.

[13] Óskarsdóttir, María & Bravo, Cristián & Verbeke, Wouter & Sarraute, Carlos & Baesens, Bart & Vanthienen, Jan. (2020). A Comparative Study of Social Network Classifiers for Predicting Churn in the Telecommunication Industry.

[14] Koumetio Tekouabou, Cédric Stéphane & Gherghina, Ştefan Cristian & Toulni, Hamza & Mata, Pedro & Martins, José. (2022). Towards Explainable Machine Learning for Bank Churn Prediction Using Data Balancing and Ensemble-Based Methods. Mathematics. 10. 2379. 10.3390/math10142379.

[15] Lee, Seonghye & Oh, Hae & Choi, Jeongil. (2020). Service Design Management and Organizational Innovation Performance. Sustainability. 13. 4. 10.3390/su13010004.

[16] Rai, Shivam & Nayak, Jogendra. (2019). Hospitality branding in emerging economies: an Indian perspective. Journal of Tourism Futures. 5. 10.1108/JTF-07-2018-0047.

[17] Han, Shaoyong. (2018). A Study on a Predictive Model of Customer Defection in a Hotel Reservation Website. MATECWeb of Conferences.228.01009. 10.1051/matecconf/201822801009.

[18] Usman, Muhammad & Azeem, Muhammad. (2018). A fuzzy-based churn prediction and retention model for prepaid customers in the telecom industry. International Journal of Computational Intelligence Systems. 11. 66-78. 10.2991/ijcis.11.1.6.

[19] Li, X.L., Li, Z. (2019). A hybrid prediction model for e-commerce customer churn based on logistic regression and extreme gradient boosting algorithm. Ingénierie des Systèmes d'Information, Vol. 24, No.

5, pp. 525-530. https://doi.org/10.18280/isi.240510

[20] Arshad, Soban & Iqbal, Khalid & Naz, Sheneela & Yasmin, Sadaf & Rehman, Zobia. (2022). A Hybrid System for Customer Churn Prediction and Retention Analysis via Supervised Learning. Computers, Materials & Continua. 72. 4283-4301.10.32604/cmc.2022.025442.

[21] Devi, M. & Saharia, Jyotikinkar & Kumar, Shubham & Chansoriya, Aayushi & Yadav, Prashant. (2019). Machine Learning Based Suspicion of Customer Detention in Banking with Diverse Solver Neighbors and Kernels. International Journal of Recent Technology and Engineering (IJRTE). 8. 3244-3249.10.35940/ijrte.D8043.118419.

[22] Zhao, Ming & Zeng, Qingjun & Chang, Ming & Tong, Qian & Su, Jiafu. (2021). A Prediction Model of Customer Churn Considering Customer Value: An Empirical Research of Telecom Industry in China. Discrete Dynamics in Nature and Society. 2021. 1-12. 10.1155/2021/7160527.

[23] Darshil Gandhi "How to Improve Retention with Churn Prediction Analytics," amplitude.com, (Accessed 28 Oct. 2023).

[24] Chu, Charles & Xu, Guandong & Brownlow, James & Fu, Bin. (2016). Deployment of a churn prediction model in financial services industry.12.10.1109/BESC.2016.7804486.

[25] [25Devi, M. & Krishna, G. & Sowmya, K. & Pavan, T.. (2019). Postulation of Customer Retention in the Banking Sector using Machine Learning and Principal Components. International Journal of Recent Technology and Engineering (IJRTE). 8. 3178-3182. 10.35940/ijrte.D8020.118419.

[26] Coussement, Kristof & Van den Poel, Dirk. (2008). Improving customer attrition prediction by integrating emotions from client/company interaction emails and evaluating multiple classifiers. Expert Systems with Applications. 36. 6127-6134. 10.1016/j.eswa.2008.07.021.

[27] Ribeiro, Hugo & Barbosa, Belem & Moreira, Antonio & Rodrigues, Ricardo. (2022). Churn in services – A bibliometric review. Cuadernos de Gestión. 22. 10.5295/cdg.211509hr.

[28] Hudaib, Amjad & Dannoun, Reham & Harfoushi, Osama & Obiedat, Ruba & Faris, Hossam. (2015). Hybrid Data Mining Models for Predicting Customer Churn. International Journal of Communications, Network and System Sciences. 08. 91-96. 10.4236/ijcns.2015.85012.

[29] Gan, Lin. (2022). XGBoost-Based E-Commerce Customer Loss Prediction. Computational Intelligence and Neuroscience. 2022. 1-10. 10.1155/2022/1858300.

[30] Bahmani, Bahram & Mohammadi, Golshan & Mohammadi, Mehrdad & Tavakkoli-Moghaddam, Reza. (2013). Customer churn prediction using a hybrid method and censored data. Management Science Letters. 3. 1345-1352. 10.5267/j.msl.2013.04.017.

[31] Ibitoye, Ayodeji & Onifade, Olufade. (2020). Blended Churn Predictive System for Quadruple-Patterned Churn Classification Towards Effective Customer Behavioural Management.6.56-59.10.11648/j.ijdst.20200602.12.

[32] Thein, Si Thu & Khin, Hnin & Thi, Aung. (2017). Anti-malarial landscape in Myanmar: Results from a nationally representative survey among community health workers and the private sector outlets in 2015/2016. Malaria Journal. 16. 10.1186/s12936-017-1761-8.

[33] Zhang, Yali & Tian, Yichao & Li, Ying & Wang, Donghua & Tao, Jin & Yang, Yongwei & Lin, Junliang & Zhang, Qiang & Wu, Luhua. (2022). Machine learning algorithm for estimating karst rocky desertification in a peak-cluster depression basin in southwest Guangxi, China. Scientific Reports. 12. 10.1038/s41598-022-21684-5.

[34] Shen, Jiquan & Shi, Jiawei & Luo, Junwei & Zhai, Haixia & Liu, Xiaoyan & Wu, Zhengjiang & Yan, Chaokun & Luo, Huimin. (2022). Deep learning approach for cancer subtype classification using high-dimensional gene expression data. BMC Bioinformatics. 23. 10.1186/s12859-022-04980-9.

[35] Li, Shujuan & Ren, Hongyan & Hu, Wensheng & Lu, Liang & xu, Xinliang & Zhuang, Dafang & Liu, Qi-Yong. (2014). Spatiotemporal Heterogeneity Analysis of Hemorrhagic Fever with Renal Syndrome in China Using Geographically Weighted Regression Models. International journal of environmental research and public health. 11. 12129-47. 10.3390/ijerph111212129.

[36] Melo, Esthefani & Nobre, Reginaldo & Pinheiro, Francisco & Souza, Leandro & Lima, Geovani & Gheyi, Hans & Elias, Jutahy & Silva, Wandra. (2018). Evaluation of West Indian cherry (Malpighia emarginata) rootstock under saline water irrigation and nitrogen fertilization. Australian Journal of Crop Science. 12. 1034-1040. 10.21475/ajcs.18.12.06.PNE1314.

[37] Behera, Tapan & Tripathi, Kumud. (2023). Root Cause Analysis Bot using Machine Learning

Techniques. 10.36227/techrxiv.21588159.v3.

[38] Rushd, Sayeed & Hafsa, Noor & Al-Faiad, Majdi & Arifuzzaman, Md. (2021). Modeling the Settling Velocity of a Sphere in Newtonian and Non-Newtonian Fluids with Machine-Learning Algorithms. Symmetry. 13. 71. 10.3390/sym13010071.

[39] Sarker, Iqbal & Hoque, Moshiul & Uddin, Kafil & Alsanoosy, Tawfeeq. (2021). Mobile Data Science and Intelligent Apps: Concepts, AI-Based Modeling and Research Directions. Mobile Networks and Applications. 26. 10.1007/s11036-020-01650-z.

[40] Sharifzadeh, Mostafa & Benali, Habib & Rivaz, Hassan. (2020). Phase Aberration Correction: A Convolutional Neural Network Approach. IEEE Access. 8. 162252-162260. 10.1109/ACCESS.2020.3021685.

[41] Iqbal, Umair & Barthélemy, Johan & Perez, Pascal. (2022). Prediction of hydraulic blockage at culverts from a single image using deep learning. Neural Computing and Applications. 34. 1-17. 10.1007/s00521-022-07593-8.

[42] Rahagiyanto, Angga & Basuki, Achmad & Sigit, Riyanto. (2017). Moment Invariant Features Extraction for Hand Gesture Recognition of Sign Language based on SIBI. EMITTER International Journal of Engineering Technology. 5. 10.24003/emitter.v5i1.173.

[43] Qin, Chuanbo & Lin, JingYin & Zeng, Junying & Zhai, Yikui & Tian, LianFang & Peng, ShuTing & Li, Fang. (2022). Joint Dense Residual and Recurrent Attention Network for DCE-MRI Breast Tumor Segmentation. Computational Intelligence and Neuroscience. 2022. 1-16. 10.1155/2022/3470764.

[44] Bao, Shuai & Liu, Jiping & Wang, Liang & Zhao, Xizhi. (2022). Application of Transformer Models to Landslide Susceptibility Mapping. Sensors. 22. 9104. 10.3390/s22239104.

[45] Sokolovsky, Artur & Hare, David & Mehnen, Jorn. (2021). Cost-Effective Vibration Analysis through Data-Backed Pipeline Optimisation. Sensors (Basel, Switzerland). 21. 10.3390/s21196678.