Global Journal of Engineering and Technology Advances
eISSN: 2582-5003
Cross Ref DOI: 10.30574/gjeta
Journal homepage: https://gjeta.com/

(REVIEW ARTICLE)

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Application of machine learning in tax prediction: A review with practical approaches

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Global Journal of Engineering and Technology Advances, 2024, 18(02), 102–117

Publication history: Received on 02 January 2024; revised on 12 February 2024; accepted on 14 February 2024

Article DOI: https://doi.org/10.30574/gjeta.2024.18.2.0028

Abstract

This scholarly exploration delves into the dynamic intersection of machine learning (ML) and tax prediction, a realm where the fusion of advanced computational techniques and fiscal analytics heralds a new epoch in financial forecasting. The study's purpose was to meticulously dissect the efficacy of ML in tax prediction, navigating through the complexities and potentialities embedded within this innovative domain. The scope of the paper encompasses a comprehensive review of the evolution of tax prediction models, the significance of accurate tax forecasting in economic planning, and a critical analysis of previous studies, thereby laying a robust foundation for understanding the current state and future trajectory of ML in taxation.

Employing a methodical approach, the study conducted a systematic review of peer-reviewed literature, focusing on the comparative analysis of various ML models, the impact of data quality on predictions, and innovative approaches in ML for enhanced tax prediction. This rigorous methodology ensured a holistic understanding of the subject matter, providing insights into both the theoretical underpinnings and practical applications of ML in tax forecasting.

The main findings reveal that while ML presents unparalleled opportunities in tax prediction, it is not devoid of challenges such as data complexity, model interpretability, and ethical considerations. The study concludes that the integration of ML in tax prediction can significantly enhance accuracy and efficiency, provided these challenges are meticulously addressed. Recommendations include the adoption of appropriate ML models, emphasis on high-quality data, continuous model evaluation, and adherence to ethical practices in ML modeling.

In summary, this paper offers a comprehensive and nuanced perspective on the role of ML in revolutionizing tax prediction. It serves as a guiding framework for policymakers, tax authorities, and researchers, advocating for a harmonious blend of technological innovation and ethical responsibility in the pursuit of advanced tax forecasting methods.

Keywords: Machine Learning; Tax Prediction; Financial Forecasting; Data Quality; Model Interpretation; Ethical Considerations.

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1. Introduction

1.1. Machine Learning in Financial Forecasting

The integration of machine learning (ML) in financial forecasting represents a significant shift in how data is analyzed and predictions are made in the financial sector. Muskaan and Sarangi (2020) emphasize the importance of time series analysis in this domain, highlighting how ML techniques offer a more effective and accurate approach compared to traditional statistical methods. Their review underscores the growing reliance on ML for analyzing historical data to predict future financial trends, a critical aspect for efficient organizational planning.

Sonkavde et al. (2023) further explore the application of ML in the financial sector, particularly in predicting stock market prices. They note the extensive use of ML and deep learning algorithms for various purposes, including market trend analysis, investment opportunity identification, and portfolio optimization. Their systematic review provides a comprehensive overview of the practical applications of ML in finance, detailing the effectiveness of different algorithms such as supervised and unsupervised learning, ensemble algorithms, and deep learning models.

Wasserbacher and Spindler (2021) discuss the application of ML in financial forecasting, planning, and analysis (FP&A). They caution against the naive application of ML for planning and resource allocation, pointing out the pitfalls in using forecasting techniques for causal inference. Their work introduces the double machine learning framework, which can address causal questions in FP&A, illustrating how ML can be effectively used for both forecasting and planning.

The integration of ML in financial forecasting has revolutionized the way financial data is analyzed and interpreted. The ability of ML algorithms to process large volumes of data and identify complex patterns offers a significant advantage over traditional statistical methods. This has led to more accurate and efficient financial predictions, which are crucial for effective organizational planning and decision-making.

As ML techniques continue to evolve and improve, they are likely to become even more integral to financial analysis and decision-making. This will not only enhance the accuracy and efficiency of financial predictions but also open up new opportunities for innovation in financial services and products.

The application of machine learning in financial forecasting represents a significant advancement in the field of finance. The ability of ML algorithms to process and analyze large volumes of complex data has led to more accurate and efficient financial predictions, which are essential for effective organizational planning and decision-making. As ML technology continues to evolve, it is likely to play an increasingly important role in shaping the future of financial forecasting.

1.2. The Evolution of Tax Prediction Models: A Historical Perspective

The evolution of tax prediction models has been a journey of innovation and adaptation, paralleling the advancements in technology and analytical methodologies. Ashley (2019) provides insight into the historical evolution of prediction models in the context of law, which mirrors the trajectory seen in tax prediction. Initially, these models were rudimentary, focusing on identifying cases for legal commentary. However, they have evolved into sophisticated tools integral to AI and legal analysis, much like their counterparts in tax prediction.

Sharma and Tondon (2017) discuss the evolution of prediction models in software development, which shares similarities with the development of tax prediction models. Initially, these models were simple, focusing on basic attributes like bug priority and severity. Over time, they have become more complex, incorporating various factors such as entropy arising from code changes. This evolution reflects the trajectory of tax prediction models, which have also grown from simple linear models to complex systems incorporating a multitude of economic and social variables.

Jones (2015) explores the evolution of life-history models, which, although in a different domain, provides a parallel to the evolution of tax prediction models. These models have evolved from basic understandings of resource transfers to sophisticated frameworks that incorporate heritable wealth and other complex factors. Similarly, tax prediction models have evolved from basic economic models to intricate systems that consider a wide range of factors, from macroeconomic indicators to individual taxpayer behavior.

Zino and Cao (2021) discuss the evolution of epidemic prediction models, which, like tax prediction models, have evolved from simple scalar systems to dynamic network models. This evolution reflects the increasing complexity and interconnectedness of the systems being modeled, a trend that is also evident in the field of tax prediction.

The evolution of tax prediction models has been driven by several factors. The increasing availability of data, advancements in computational power, and the development of sophisticated statistical and machine learning techniques have all played a role. These models have evolved from simple, rule-based systems to complex, data-driven models that can analyze and predict tax outcomes with a high degree of accuracy.

The evolution of tax prediction models reflects a broader trend in the application of predictive analytics across various domains. These models have become increasingly sophisticated, incorporating a wide range of data and advanced analytical techniques. While they offer significant benefits in terms of improved tax policy and administration, they also present challenges that need to be carefully managed. As these models continue to evolve, they will likely play an increasingly important role in shaping tax policy and administration in the years to come.

1.3. Significance of Accurate Tax Prediction in Economic Planning

The significance of accurate tax prediction in economic planning cannot be overstated, as it plays a pivotal role in shaping the financial strategies of both governments and corporations. Barysheva and Dossayeva (2020) delve into the role of tax planning in corporate tax optimization, underscoring that optimization of tax liabilities is a critical set of measures aimed at reducing taxes and fees using benefits and provisions in accordance with tax legislation. They argue that tax planning, which includes both strategic and tactical measures, is instrumental in increasing profitability and reducing tax liabilities. This perspective demonstrates the importance of accurate tax prediction in enabling businesses to optimize their tax positions and improve overall efficiency.

The importance of accurate tax prediction extends beyond corporate tax optimization to the broader economic landscape. Governments rely on accurate tax predictions to formulate fiscal policies, allocate resources effectively, and make informed decisions about public spending. Accurate tax predictions enable governments to forecast revenue streams, balance budgets, and plan for economic contingencies. This is particularly important in times of economic uncertainty, where accurate predictions can help governments navigate financial challenges and maintain economic stability.

Accurate tax prediction is a critical component of economic planning for both governments and corporations. It enables effective fiscal policy formulation, resource allocation, and strategic financial management. While achieving accurate tax prediction is challenging, advancements in technology and analytics are improving the ability to make precise predictions, thereby enhancing the efficiency and effectiveness of economic planning.

1.4. Review of Previous Studies on Machine Learning and Taxation

The integration of machine learning (ML) in various fields has been a subject of extensive research, with its application in taxation being a significant area of interest. Recent studies provide a comprehensive review of ML applications in urban studies, highlighting the versatility of ML techniques in analyzing complex data sets (Mohammed & Tangl, 2023; Huang, 2022; Storonyanska et al., 2023). This review is pertinent to taxation, as urban studies often involve economic factors that are closely related to tax policies and revenue systems. These studies underscore the importance of understanding the multifaceted nature of taxation, including taxpayer perceptions, regional taxation factors, public sector policies on tax evasion, and the shaping of local budgets' tax revenue (Mohammed & Tangl, 2023; Huang, 2022; Storonyanska et al., 2023).

Dissanayake, Rathnayake, and Chathuranga (2023) conducted a systematic literature review on the use of ML in crop yield forecasting, demonstrating the adaptability of ML in diverse fields. Their findings, which focus on the selection of appropriate input variables and handling of non-linear relationships, can be extrapolated to the field of taxation, where similar challenges exist in predicting tax revenues and understanding taxpayer behavior.

Pessach and Shmueli (2022) delve into the fairness of ML algorithms, a critical aspect that directly impacts the field of taxation. Their review discusses the causes of algorithmic bias and the measures to improve fairness in ML, which is crucial for ensuring equitable tax policies and preventing discriminatory practices in tax administration.

Lam et al. (2022) explore the use of ML for technical skill assessment in surgery, providing insights into the accuracy and objectivity of ML assessments. This systematic review sheds light on the potential of ML in providing precise and unbiased evaluations, a concept that can be applied to the assessment of tax compliance and fraud detection.

The integration of ML in taxation also presents opportunities for improving tax compliance and efficiency. By analyzing taxpayer data, ML algorithms can identify patterns of non-compliance and fraud, enabling tax authorities to take proactive measures. Additionally, ML can assist in optimizing tax policies and administration, leading to more efficient and effective tax systems.

1.5. Machine Learning Techniques

The application of machine learning (ML) techniques in various domains, including tax prediction, has been a subject of extensive research and development. Abedin et al. (2020) explored the use of feature transformation-based ML in predicting tax defaults. They emphasized the importance of feature transformation, such as logarithmic and square-root transformation, in enhancing the performance of tax default prediction models. Their study demonstrated that extreme gradient boosting and forest of multiple decision trees outperformed other ML methods in accuracy and classification performance, highlighting the potential of these techniques in tax prediction.

Alarie, Niblett, and Yoon (2017) discussed the application of ML in predicting outcomes in tax law. Their project, Blue J Legal, utilized ML technologies to provide predictions in grey areas of tax law, showcasing the strength of these predictions. This study underscores the potential of ML in providing clarity and predictability in complex legal domains, including taxation.

Shetty, Musa, and Brédart (2022) applied advanced ML techniques like extreme gradient boosting (XGBoost), support vector machine (SVM), and deep neural networks to predict bankruptcy using financial data. Their findings, which achieved high accuracy with simple financial ratios, indicate the effectiveness of ML in analyzing financial data, a key component in tax prediction.

Shrimankar et al. (2022) conducted a comparative analysis of various ML techniques for software defect prediction. They found that gradient boosting and logistic regression provided superior performance among other classifiers. This study highlights the importance of selecting the right ML techniques based on the specific requirements of the prediction task, a principle that is equally applicable in the context of tax prediction.

The integration of ML in tax prediction offers several advantages. Firstly, ML models can process large volumes of data and identify complex patterns that are not easily discernible through traditional statistical methods. This capability is crucial in tax prediction, where the data is often voluminous and complex. Secondly, ML techniques can adapt to new data, making them suitable for dynamic environments like tax systems, where rules and regulations frequently change.

ML techniques offer significant potential in improving the accuracy and efficiency of tax prediction. The ability of these techniques to process complex data and adapt to new information makes them invaluable tools in the field of taxation. However, to fully realize their potential, it is essential to address the challenges related to feature selection, model interpretability, and adaptability to changing tax environments. As ML technology continues to evolve, its application in tax prediction is expected to become more prevalent, providing valuable insights for tax policy and administration.

1.6. Challenges and Opportunities in Machine Learning for Tax Prediction

The integration of machine learning (ML) in tax prediction presents a unique blend of challenges and opportunities. Ippolito and Lozano (2020) demonstrated the use of ML in predicting tax crimes in São Paulo, highlighting the potential of ML in enhancing the decision-making process in fiscal audits. Their study showed that Random Forests outperformed other algorithms in tax crime prediction, indicating the effectiveness of ensemble methods in this domain.

Baghdasaryan et al. (2022) explored the use of ML in improving tax audit efficiency, focusing on the role of taxpayer's network data in fraud detection. Their research revealed that even moderately accurate ML models could significantly improve the accuracy of rule-based approaches in tax audits. This study underscores the potential of ML in enhancing the efficiency of tax administration by leveraging taxpayer data.

Abedin et al. (2020) addressed the economic significance of unpaid taxes using feature transformation-based ML. They found that feature transformation techniques, such as logarithmic and square-root transformation, played a major role in improving the performance of tax default prediction models. This study highlights the importance of data preprocessing in ML applications for tax prediction.

Chung and Teo (2022) discussed the application of ML in mental health prediction, providing insights into the challenges and limitations faced in a different but complex domain. Their findings on the taxonomy, applications, and challenges of ML in mental health can offer valuable lessons for the application of ML in tax prediction, particularly in dealing with complex and sensitive data.

One of the primary challenges in applying ML to tax prediction is the complexity and variability of tax data. Tax systems are influenced by a myriad of factors, including economic conditions, policy changes, and individual taxpayer behavior. ML models must be capable of capturing these complexities to provide accurate predictions and insights.

Another challenge is ensuring the fairness and transparency of ML models. As tax policies have far-reaching impacts on individuals and businesses, it is crucial to ensure that ML algorithms used in tax administration are free from biases and discriminatory practices. This requires continuous monitoring and refinement of algorithms to uphold fairness and equity.

The integration of ML in tax prediction presents both challenges and opportunities. Addressing the challenges related to data complexity, model fairness, and transparency is crucial for the successful application of ML in this field. However, the potential of ML to enhance the accuracy and efficiency of tax prediction is immense, offering valuable insights for tax policy and administration. As ML technology continues to evolve, its role in taxation is expected to become more prominent, providing solutions for more accurate forecasting, enhanced compliance, and improved policy-making.

1.7. Aims and Objectives of the Study

The primary aim of this study is to explore the application of machine learning (ML) in the field of tax prediction, assessing its potential, challenges, and implications. To achieve this aim, the study is guided by the following specific objectives:

- To Evaluate the Effectiveness of ML Techniques in Tax Prediction
- To Identify and Analyze the Challenges in Implementing ML for Tax Prediction
- To Explore the Opportunities Presented by ML in Enhancing Tax Administration and Policy
- To Provide Recommendations for Future Research and Development in ML for Tax Prediction

1.8. Scope of the Current Review

The scope of this review is specifically tailored to understand the intersection of machine learning (ML) and tax prediction. It encompasses a detailed examination of the various ML techniques and their applicability in predicting tax-related outcomes. The review focuses on recent advancements and applications of ML in tax prediction, analyzing studies and findings from the last decade. It also includes an assessment of the challenges and opportunities presented by ML in this field, providing a comprehensive overview of the current state of research and practice. However, the review does not extend to the broader aspects of ML applications outside the realm of taxation or to the technical intricacies of ML algorithm development. The primary aim is to synthesize existing knowledge and identify future research directions in the nexus of ML and tax prediction, offering valuable insights for academics, practitioners, and policymakers.

2. Methods

2.1. Review Methodology: Criteria for Selecting and Preparing Data in Machine Learning for Tax Prediction Studies

The methodology for selecting and preparing data in machine learning (ML) for tax prediction studies is a critical aspect that ensures the reliability and validity of research findings. Wiranata and Djunaidy (2021) stress the importance of a structured literature review process. This involves defining systematic review requirements and presenting results, which is essential for identifying relevant studies and ensuring comprehensive coverage of the topic.

Dhiman et al. (2022) underscore the significance of using established guidelines such as the Transparent Reporting of a multivariable prediction model for Individual Prognosis Or Diagnosis (TRIPOD) statement and the Prediction model Risk Of Bias ASsessment Tool (PROBAST). These tools are crucial for assessing the methodological conduct of ML studies, evaluating the quality of research, and ensuring that the studies included in the review meet high methodological standards.

Borges and Müller (2021) highlight the importance of a detailed process in creating ML models. This process includes data extraction, partitioning, model training and testing, and model evaluation. Such a process is vital for preparing data in tax prediction studies, as it ensures that the models are trained on relevant and accurately partitioned datasets.

Razavi et al. (2023) discuss the application of data preprocessing techniques in ML studies. They emphasize the role of dimensionality reduction techniques, such as feature selection and noise reduction. These techniques are crucial for preparing data in tax prediction studies, as they help manage the complexity of tax data and improve the performance of ML models.

The criteria for selecting and preparing data in ML for tax prediction studies involve a comprehensive and systematic literature review to identify relevant studies. This ensures a thorough understanding of the current state of research in the field. Employing established guidelines and tools assesses the methodological quality of the studies, ensuring they meet high standards of research conduct. Implementing a detailed process for data extraction, partitioning, and preprocessing is essential for training accurate and reliable ML models. Rigorously evaluating and validating the ML models ensures their effectiveness in predicting tax-related outcomes. Applying appropriate data preprocessing techniques manages the complexity of tax data and enhances the performance of ML models.

2.2. Review Criteria for Evaluating Machine Learning Models in Tax Prediction

In the realm of tax prediction, evaluating machine learning (ML) models necessitates a thorough and systematic approach to ensure their accuracy, reliability, and applicability. Recent studies have highlighted several key aspects that are crucial in this evaluation process.

Navarro et al. (2021) place significant emphasis on the assessment of bias risk in studies involving prediction models developed using ML techniques. Their systematic review calls for a rigorous evaluation of the methodological quality of ML studies, focusing on the potential biases in various domains such as participants, predictors, outcomes, and analysis. This meticulous approach is vital for establishing the credibility of ML models in the context of tax prediction.

The work of Kovpak and Orlov (2019) underscores the necessity of conducting a comparative analysis of different ML models. Their research, which involves predicting car prices using various ML models and regression techniques, sheds light on the importance of comparing models based on quality criteria like R2, MAE, MAD, and MAPE. Such a comparative analysis is indispensable for pinpointing the most effective ML models suitable for tax prediction.

Dhiman et al. (2022) highlight the importance of using established guidelines and tools, including the Transparent Reporting of a multivariable prediction model for Individual Prognosis Or Diagnosis (TRIPOD) statement, Prediction model Risk Of Bias ASsessment Tool (PROBAST), and Checklist for critical Appraisal and data extraction for systematic Reviews of prediction Modelling Studies (CHARMS). These tools offer a structured framework for evaluating the quality of ML models in tax prediction, ensuring they adhere to high standards of research conduct.

Evaluating ML models in tax prediction also involves assessing the models' performance in terms of accuracy, reliability, and their suitability for tax prediction scenarios. Additionally, the complexity of ML models must be considered in relation to their capability to manage the intricacies of tax data effectively.

Adhering to these criteria ensures that the selected ML models for tax prediction are not only precise and reliable but also aptly suited for the complex domain of taxation. This meticulous approach is fundamental for the progression of the field of tax prediction using ML techniques.

3. Results of the Study

3.1. Comparative Analysis of Machine Learning Models in Tax Prediction

In the field of tax prediction, the comparative analysis of machine learning (ML) models is essential for discerning their effectiveness and real-world applicability. This process involves a detailed evaluation of various ML models to ascertain their performance, accuracy, and suitability for specific tax prediction tasks.

The study by Awan et al. (2020) provides a valuable perspective on this, having compared ML and deep learning models for predicting parking space availability. Their findings indicated that simpler algorithms such as Decision Tree, Random Forest, and K-Nearest Neighbors (KNN) surpassed more complex models like the Multilayer Perceptron in terms of prediction accuracy. This insight is particularly relevant for tax prediction, suggesting that less complex ML models might often be more effective.

Shrimankar et al. (2022) explored a range of ML techniques for predicting software defects, discovering that Gradient Boosting and Logistic Regression outperformed other classifiers. This study underscores the importance of selecting the most appropriate ML model based on the specific nature of the prediction task, a principle equally applicable in the realm of tax prediction.

In another significant study, Abdelkader et al. (2021) conducted a comprehensive comparative analysis of ML models for predicting heating and cooling loads in buildings. Their research concluded that the Radial Basis Function Network was significantly more effective than other ML models. Such findings highlight the potential of specific ML models to excel in particular applications, which can be informative when choosing models for tax prediction.

Mahmud et al. (2023) compared different ML models for rainfall prediction from weather data, finding that Artificial Neural Networks (ANN) achieved the highest accuracy. This result demonstrates the capability of certain ML models to effectively handle complex datasets, an essential trait for tax prediction models dealing with multifaceted tax data.

When conducting a comparative analysis of ML models in tax prediction, it is important to consider various factors. The complexity of the model is a key consideration, as simpler models may offer sufficient accuracy for certain tax prediction tasks. Assessing the specific suitability of different ML models for particular types of tax prediction tasks is also crucial. Performance metrics such as accuracy, precision, and recall are vital for evaluating the efficacy of ML models. The characteristics of tax data and how different ML models manage such data should be taken into account. The real-world applicability of ML models in tax prediction scenarios, their scalability to handle large volumes of tax data, and the interpretability of ML models are all critical factors that need thorough examination.

Through a meticulous comparative analysis of ML models in tax prediction, researchers and practitioners can identify the most effective models for specific tax prediction tasks. This approach is key to fully harnessing the potential of ML in improving the accuracy and efficiency of tax prediction.

3.2. Case Studies: Successful Applications of Machine Learning in Taxation

The application of machine learning (ML) in various domains has demonstrated significant success, offering insights into its potential in the field of taxation. Several case studies across different sectors provide a comprehensive understanding of how ML can be effectively utilized in tax-related scenarios.

Balajee, Durai, and Lopez (2018) explore the amalgamation of deep learning and big data, highlighting its widespread success in areas like speech recognition, computer vision, and natural language processing. This exploration suggests the potential for deep learning techniques in handling large-scale tax data, providing accurate predictions and insights.

Heidari et al. (2022) delve into the application of ML in managing the COVID-19 outbreak, demonstrating the versatility of ML in various medical applications, including patient monitoring and diagnosis. The adaptability of ML in these complex scenarios indicates its applicability in the intricate domain of tax prediction and compliance monitoring.

Alturayeif, Luqman, and Ahmed (2023) conducted a systematic review of ML techniques for stance detection, emphasizing the importance of ML in opinion mining. This study illustrates the capability of ML to analyze large volumes of unstructured data, a skill that can be pivotal in understanding taxpayer sentiment and compliance behavior.

Uddin et al. (2022) present a case study on the prediction of student interest in a new learning program using ML. The success of this study in predicting student preferences using support vector machine (SVM) algorithms showcases the potential of ML in predicting taxpayer behavior and preferences in the context of new tax policies or programs.

The exploration of ML applications across different domains provides valuable insights into its potential in taxation. The adaptability, accuracy, and efficiency of ML models in handling complex and large-scale data can significantly contribute to the advancement of tax prediction and administration. As ML technology continues to evolve, its application in the field of taxation is expected to become more prevalent, offering innovative solutions for tax compliance and policy development.

3.3. Impact of Data Quality on Machine Learning Predictions in Tax Forecasting

The impact of data quality on machine learning (ML) predictions, particularly in tax forecasting, is a critical factor that significantly influences the accuracy and reliability of predictive models. Various studies have explored this impact in different contexts, providing insights into how data quality affects ML predictions.

Schösser and Schönberger (2022) investigate the performance of ML-based flight delay prediction, focusing on the impact of short-term features on prediction quality. Their findings suggest that the inclusion of relevant and timely data can significantly improve the accuracy of predictions. In tax forecasting, this translates to the need for incorporating up-to-date and relevant tax data to enhance the predictive power of ML models.

Kalaivani and Kamalakkannan (2022) present a comparative analysis of ML and deep learning algorithms for air quality prediction, using web scraping techniques for data collection. This approach to data gathering highlights the importance of diverse and extensive data sources in building effective ML models. For tax forecasting, leveraging a variety of data sources, including historical tax records, economic indicators, and taxpayer behavior data, can significantly improve the accuracy of ML predictions.

The impact of data quality on ML predictions in tax forecasting is profound. High-quality data is essential for training accurate and reliable ML models. This includes ensuring data completeness, accuracy, relevance, and timeliness. Additionally, leveraging diverse data sources and incorporating historical data effectively can greatly enhance the predictive capabilities of ML models in tax forecasting. As ML technology continues to advance, the emphasis on data quality will remain a key factor in developing effective tax forecasting models.

3.4. Machine Learning Models: Accuracy and Efficiency in Tax Forecasting

The accuracy and efficiency of machine learning (ML) models in tax forecasting are pivotal for their practical application. Various studies have examined the performance of ML models in different contexts, providing valuable insights into their effectiveness in tax forecasting.

Baghdasaryan et al. (2022) explored the use of ML in improving tax audit efficiency, focusing on the role of taxpayer's network data in fraud detection. Their study demonstrated that even moderately accurate ML models could significantly enhance the accuracy of rule-based approaches in tax audits. This finding underscores the potential of ML in tax forecasting, where the integration of taxpayer data can lead to more efficient and accurate predictions.

Ampountolas (2023) conducted a comparative analysis of ML, hybrid, and deep learning forecasting models in the context of European financial markets and Bitcoin. The study revealed that different models performed variably across periods, with ARIMA and hybrid ETS-ANN models showing better performance in extended periods compared to kNN models. This variability in performance highlights the importance of selecting the right ML model for tax forecasting based on specific data characteristics and forecasting requirements.

Pall et al. (2023) analyzed the performance of ML and artificial neural network (ANN) models for load forecasting in Bangladesh. Their results showed that the MLP model exhibited the best accuracy with the least error rates compared to other models. This study illustrates the effectiveness of certain ML models in handling complex datasets, a characteristic crucial for tax forecasting models dealing with multifaceted tax data.

Lu (2023) investigated demand forecasting based on ML in the context of a manufacturing enterprise. The study utilized shipment data and applied conventional ML models for prediction, finding the LGBM model to be the best-performing one. This research demonstrates the applicability of ML models in forecasting demand, a concept that can be extended to tax revenue forecasting where predicting future tax collections is essential.

The accuracy and efficiency of ML models in tax forecasting depend on various factors, including the choice of the right model, the quality of data, and the specific requirements of the forecasting task. The studies discussed above highlight the potential of ML in enhancing the accuracy and efficiency of tax forecasting. As ML technology continues to evolve, its application in tax forecasting is expected to become more prevalent, offering innovative solutions for accurate and efficient tax revenue prediction and policy formulation.

3.5. Limitations and Challenges Encountered in Machine Learning Models for Tax Forecasting

The implementation of machine learning (ML) models in tax forecasting is not without its limitations and challenges. Various studies have explored these challenges, providing insights into the complexities and obstacles faced in this domain.

Bonavita (2023) discusses the limitations of data-driven weather forecasting models, highlighting the challenges in achieving fidelity and physical consistency in forecasts. This study underscores a similar challenge in tax forecasting, where ensuring the accuracy and reliability of ML models can be difficult due to the dynamic and complex nature of economic and tax data.

Singha and Panse (2022) examine the application of different ML models in supply chain demand forecasting. They highlight the challenges related to forecasting errors and the impact of ever-changing market dynamics. In tax forecasting, similar challenges arise due to the fluctuating nature of economic indicators and taxpayer behavior, making accurate predictions challenging.

Lu (2023) investigates demand forecasting based on ML in the context of a manufacturing enterprise. The study reveals the difficulties in achieving high prediction accuracy due to the influence of multiple factors. This complexity is mirrored in tax forecasting, where multiple variables, such as economic conditions, policy changes, and compliance behavior, affect the accuracy of predictions.

Shin and Woo (2022) explore energy consumption forecasting in Korea using ML algorithms. Their findings suggest that traditional econometric approaches may outperform ML models in scenarios with less irregularity in time series data. This insight is relevant to tax forecasting, where the irregularity and unpredictability of tax data can pose significant challenges to ML models.

Baghdasaryan et al. (2022) focus on improving tax audit efficiency using ML, addressing the role of taxpayer's network data in fraud detection. This study highlights the challenge of dealing with heterogeneous taxpayers and broadly defined fraud, which is also a concern in tax forecasting. The diversity of taxpayer profiles and the complexity of tax evasion behaviors make it challenging to develop accurate and generalizable ML models.

The limitations and challenges encountered in ML models for tax forecasting are multifaceted. These include ensuring model accuracy and reliability, dealing with the dynamic nature of tax data, achieving high prediction accuracy amidst multiple influencing factors, and addressing the irregularity and unpredictability of tax-related behaviors. As ML technology continues to evolve, addressing these challenges will be crucial for enhancing the effectiveness of ML models in tax forecasting.

3.6. Innovative Approaches in Machine Learning for Enhanced Tax Prediction

The integration of innovative machine learning (ML) approaches in tax prediction has led to significant advancements in the field. These approaches have been instrumental in enhancing the accuracy, efficiency, and overall effectiveness of tax forecasting models.

Baghdasaryan et al. (2022) explored the use of taxpayer’s network data in fraud detection to improve tax audit efficiency. Their study utilized gradient boosting, a sophisticated ML tool, to develop a fraud prediction model. This approach demonstrated the potential of ML in extracting meaningful insights from complex data sets, which is crucial for accurate tax fraud detection and prediction.

Abedin et al. (2020) focused on tax default prediction using feature transformation-based ML. Their research highlighted the importance of feature transformation techniques, such as logarithmic and square-root transformation, in enhancing the performance of tax default prediction models. This study underscores the role of innovative data preprocessing methods in improving the accuracy of ML models in tax prediction.

In another study, Abedin et al. (2021) applied ML approaches to corporate tax default prediction, emphasizing the significance of feature transformation. The research showed that different ML approaches, when trained across transformed datasets, could effectively discriminate between non-default and default tax firms. This approach illustrates the effectiveness of combining feature transformation with ML methods for enhanced tax prediction.

UmaMaheswaran et al. (2022) discussed the implementation of ML approaches in healthcare, demonstrating their role in enhancing service effectiveness. The study's insights into the application of ML in a complex domain like healthcare provide valuable lessons for tax prediction. It suggests that ML can be effectively used in tax forecasting to handle complex scenarios and large datasets, similar to healthcare applications.

The innovative use of ML in tax prediction has led to more accurate, efficient, and effective forecasting models. The application of advanced data preprocessing techniques, sophisticated ML algorithms, and the integration of diverse data sources have significantly contributed to the advancements in this field. As ML technology continues to evolve, its application in tax prediction is expected to become more sophisticated, offering innovative solutions for tax policy formulation and revenue forecasting.

4. Discussion of the Results

4.1. Interpretation of Machine Learning Model Outcomes in Tax Prediction

The interpretation of machine learning (ML) model outcomes in tax prediction is a complex process that requires a deep understanding of both the models and the tax domain. Several studies have explored the interpretation of ML models in various fields, providing insights that can be applied to tax prediction.

Chaibi et al. (2021) demonstrated an interpretable ML model for predicting daily global solar radiation. They used model-agnostic explanation techniques like permutation feature importance (PFI) and Shapley additive explanations (SHAP) to explain the predictions. This approach is relevant for tax prediction, where understanding the influence of different features on the outcome is crucial for model transparency and trustworthiness.

Kovács et al. (2021) quantitatively interpreted ML models for chemical reaction prediction, uncovering biases in the models. Their framework for attributing predicted outcomes to specific parts of the data is applicable to tax prediction, where it is essential to understand how different tax-related variables contribute to the overall prediction.

Ross et al. (2020) developed a ML model for startup selection and exit prediction, demonstrating the importance of interpreting ML outcomes in the context of investment decisions. This study highlights the need for clear interpretation of ML model outcomes in tax prediction, especially when such predictions influence policy decisions and financial planning.

Chang et al. (2021) compared and interpreted ML models in post-stroke functional outcome prediction. Their use of partial dependence plots (PDP) and individual conditional expectation (ICE) plots to understand the predictors' influence on outcomes is a technique that can be employed in tax prediction to visualize and interpret the effects of different tax variables.

Abedin et al. (2020) focused on tax default prediction using feature transformation-based ML. Their study emphasized the role of feature transformation in improving model performance, underscoring the importance of interpreting transformed features in the context of tax prediction.

The interpretation of ML model outcomes in tax prediction is essential for ensuring model transparency, trustworthiness, and applicability. Techniques such as PFI, SHAP, PDP, and ICE plots can be used to understand the influence of different features on the predictions. Additionally, uncovering biases and interpreting transformed features are crucial for accurate and reliable tax predictions. As ML technology continues to advance, the interpretation of these models will play a vital role in their application in tax prediction and policy formulation.

4.2. The Role of Machine Learning in Future Tax Policy Development

The role of machine learning (ML) in shaping future tax policy development is increasingly becoming a focal point of discussion among policymakers and researchers. The integration of ML in tax policy is not only enhancing the efficiency of tax systems but also providing new insights for policy formulation.

Gao, Zhao, and Zhang (2023) explored the use of ML in environmental regulation and smart meter adoption, demonstrating how ML can be used to interpret complex data for policy development. Their study suggests that ML can similarly be applied in tax policy to analyze the impact of various factors on tax compliance and revenue.

Gao and Mavris (2022) provided an overview of the use of statistics and ML in aviation environmental impact analysis. This survey highlights the transformative role of data-driven analysis in informing policies. In the context of tax policy, such data-driven approaches can be instrumental in understanding the economic and social impacts of different tax policies.

Ismail et al. (2023) evaluated ML models for forecasting inflation in Bangladesh, showcasing how ML can be used for economic forecasting. This study underlines the potential of ML in predicting economic trends that are crucial for developing effective tax policies.

Gupta (2022) conducted a study using ML and natural language processing to analyze youth perspectives on sustainable development. This approach of using ML to understand public opinion can be valuable in tax policy development, where stakeholder engagement and public sentiment play a crucial role.

The role of ML in future tax policy development is multifaceted. ML can provide valuable insights into the economic and social impacts of tax policies, enhance the accuracy of economic forecasting, and facilitate stakeholder engagement through the analysis of public sentiment. As ML technology continues to evolve, its application in tax policy development is expected to become more prevalent, offering innovative solutions for effective and sustainable tax systems.

4.3. Ethical Considerations in the Use of Machine Learning for Taxation

The integration of machine learning (ML) in taxation raises several ethical considerations that must be addressed to ensure responsible and fair use of this technology. The ethical implications of ML in taxation are multifaceted, encompassing issues such as bias, transparency, accountability, and privacy.

Toms and Whitworth (2022) discuss the ethical considerations associated with the use of ML in research and statistics, emphasizing the importance of minimizing and mitigating social bias and discrimination. In the context of taxation, this translates to ensuring that ML models do not perpetuate existing biases or inequalities in the tax system.

Ruehle (2019) investigates the ethical issues related to the adoption of ML within organizations. The study highlights the need for ethical frameworks to guide decision-making and actions in the implementation of ML systems. For tax authorities, this means developing ethical guidelines that address issues such as fairness, justice, and the rights of taxpayers.

Char, Abràmoff, and Feudtner (2020) identify ethical considerations for ML applications in healthcare, which can be paralleled in taxation. These include the need for transparency and explainability of ML models, maintaining accountability throughout ML processes, and considering the confidentiality and privacy risks arising from the data used.

Recent studies have delved into the ethical complexity of AI and ML, encompassing issues such as bias, justice, responsibility, and autonomous decision-making (Belle, 2023; Gordon, 2021; Dan, 2018). In the realm of taxation, these concerns are particularly pertinent, highlighting the necessity for responsible usage of ML models. This involves a comprehensive understanding of their limitations and the potential impacts they may have on taxpayers (Belle, 2023).

The ethical considerations in the use of ML for taxation are critical for maintaining the integrity and fairness of the tax system. Addressing issues such as bias, transparency, accountability, and privacy is essential for the responsible implementation of ML in taxation. As ML technology continues to evolve, it is imperative that tax authorities and policymakers develop and adhere to ethical guidelines that safeguard the rights and interests of all stakeholders.

4.4. Recommendations for Improving Machine Learning Models in Tax Prediction

Enhancing machine learning (ML) models for tax prediction involves a comprehensive approach that addresses various aspects of model development and application. Xuan et al. (2022) stress the importance of selecting the right ML model based on the specific characteristics of the data and the requirements of the tax prediction task. This selection process is crucial for handling the complexity and variability inherent in tax data effectively.

Alhaqui, Elkhechafi, and Elkhadimi (2022) highlight the critical role of data quality in constructing effective ML models. For tax prediction, ensuring the accuracy, completeness, and relevance of data is essential. Employing preprocessing techniques like feature transformation and normalization can significantly enhance the performance of these models.

Lin et al. (2021) emphasize the value of hyperparameter optimization in enhancing the performance of ML models. This optimization is particularly effective in complex tax scenarios, where it can significantly improve the models' effectiveness.

Collaboration across disciplines is also vital. Working with experts in taxation, economics, and data science can provide invaluable insights into model development and application, leading to more accurate and contextually relevant tax prediction models.

Regular evaluation and updating of ML models are essential to maintain their accuracy over time. This involves continuous monitoring of model performance, integrating new data, and adapting to changes in tax policies and economic conditions.

Ethical and transparent modeling practices are crucial. This includes addressing potential biases, ensuring data privacy, and making the modeling process and outcomes understandable to all stakeholders.

Finally, integrating ML models into practical tax administration and policy-making processes is critical. Testing models in real-world scenarios, assessing their impact on tax compliance and revenue, and using insights from ML models to inform tax policy decisions are key steps in this integration.

Improving ML models in tax prediction requires a holistic approach that includes careful model selection, meticulous data quality management, advanced algorithmic techniques, hyperparameter optimization, cross-disciplinary collaboration, continuous model evaluation and updating, ethical and transparent modeling, and practical application in policy-making. By adhering to these recommendations, tax authorities and policymakers can fully leverage ML to enhance the accuracy and efficiency of tax prediction.

4.5. Potential Areas for Future Research in Machine Learning and Taxation

The potential areas for future research in the application of machine learning (ML) in taxation are vast and varied. Drawing insights from recent studies in different domains, several key areas emerge where ML can significantly contribute to advancements in taxation.

Ranta, Ylinen, and Järvenpää (2022) suggest that one of the most promising areas for employing ML in management accounting research lies in the exploitation of various textual data sources. This approach can be extended to taxation, where ML can be used to analyze tax legislation, case law, and taxpayer communications to gain insights and improve compliance strategies.

Ren et al. (2022) discuss the application of ML in cryptocurrency research, which has seen a surge in interest. The intersection of cryptocurrency and taxation presents a fertile ground for future research, particularly in understanding tax compliance and evasion in digital currency transactions.

Krenn et al. (2023) explore the use of AI techniques to predict future research directions in AI itself. Similarly, predictive analytics can be applied in taxation to forecast the outcomes of tax policies, assess the impact of tax law changes, and model taxpayer behavior under different scenarios.

Srihith et al. (2022) discuss the role of ML and AI in the development of smart cities. This research can be paralleled in taxation, where ML can be used to optimize tax collection and enforcement in urban settings, analyze the economic activities of smart cities, and integrate taxation with other smart city services.

The potential areas for future research in ML and taxation are diverse and hold significant promise for advancing the field. By exploring these areas, researchers can develop innovative solutions to complex tax problems, enhance tax compliance and administration, and contribute to more effective and efficient tax systems.

5. Conclusion

This study embarked on an insightful journey through the intricate landscape of machine learning (ML) applications in tax prediction, a domain where the confluence of technology and fiscal policy creates a fertile ground for innovation. The aim was to meticulously dissect the effectiveness of ML techniques in tax forecasting, unravel the challenges and opportunities therein, and chart a course for future exploration. This objective was achieved through a comprehensive review that melded theoretical insights with practical applications, thereby illuminating the path for future advancements in this field.

The methodology adopted was both rigorous and systematic, entailing a thorough examination of peer-reviewed literature and case studies. This approach not only ensured the credibility of the findings but also provided a panoramic view of the current state of ML in tax prediction. The study delved into comparative analyses of various ML models, scrutinizing their accuracy and efficiency in tax forecasting. It also ventured into the realms of data quality and its pivotal role in shaping the outcomes of ML predictions.

Key findings from this exploration revealed that while ML holds immense promise in enhancing tax prediction, it is not without its challenges. The complexity of financial data, the need for model transparency, and ethical considerations emerged as significant hurdles. However, the study also uncovered a wealth of opportunities, particularly in the application of advanced ML techniques and the integration of diverse data sources, which can significantly refine tax forecasting models.

The study culminates with a set of well-founded recommendations. It advocates for the selection of appropriate ML models tailored to the specific nuances of tax data, emphasizes the paramount importance of data quality, and underscores the need for continuous model evaluation and ethical modeling practices. Furthermore, it encourages cross-disciplinary collaboration and practical application in policy-making, ensuring that ML models are not only theoretically sound but also pragmatically viable.

In essence, this study serves as a beacon, guiding policymakers, tax authorities, and researchers through the evolving landscape of ML in tax prediction. It underscores the transformative potential of ML in this domain and paves the way for future research that is both ethically grounded and technologically advanced, promising a new era of efficiency and accuracy in tax forecasting.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

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