Asian Journal of Economics, Business and Accounting

Volume 24, Issue 11, Page 503-513, 2024; Article no.AJEBA.126796
ISSN: 2456-639X

Transforming Tax Compliance with Machine Learning: Reducing Fraud and Enhancing Revenue Collection

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Authors' contributions

This work was carried out in collaboration among all authors. All authors read and approved the final manuscript.

Article Information

DOI: https://doi.org/10.9734/ajeba/2024/v24i111572

Open Peer Review History:
This journal follows the Advanced Open Peer Review policy. Identity of the Reviewers, Editor(s) and additional Reviewers, peer review comments, different versions of the manuscript, comments of the editors, etc are available here: https://www.sdiarticle5.com/review-history/126796

Review Article

Received: 11/09/2024
Accepted: 14/11/2024
Published: 18/11/2024

ABSTRACT

The integration of machine learning (ML) in tax administration has the potential to revolutionize tax compliance, enhancing fraud detection and optimizing revenue collection. This literature review explores the application of ML in tax systems, emphasizing its transformative role in addressing the limitations of traditional, labor-intensive compliance methods. Justification for adopting a literature

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Cite as: *Olabanji, Samuel Oladiipo, Oluwaseun Oladeji Olaniyi, and Olugbenga Olaposi Olaoye. 2024. "Transforming Tax Compliance With Machine Learning: Reducing Fraud and Enhancing Revenue Collection". Asian Journal of Economics, Business and Accounting 24 (11):503-13. https://doi.org/10.9734/ajeba/2024/v24i111572.*

review approach is rooted in the need to consolidate diverse perspectives, address research gaps, and provide an informed synthesis of existing findings. The study highlights the criteria used for selecting case studies and research papers, ensuring a robust analysis of ML's ability to automate detection processes, improve risk assessment, and enable predictive analytics for efficient tax administration. Despite its potential, ML adoption is challenged by data quality issues, privacy concerns, technical infrastructure demands, and ethical considerations, which must be systematically addressed. This paper also identifies literature gaps, particularly the lack of balanced discourse, and provides recommendations for overcoming barriers, including enhancing data management practices, adopting ethical frameworks, and fostering cross-border collaboration. By addressing these challenges, ML can equip tax authorities with tools for creating efficient, adaptive, and fair systems. This research underscores ML's growing importance in transforming global tax compliance, setting the stage for a future of more responsive and effective revenue administration.

Keywords: Machine learning; tax compliance; fraud detection; revenue collection; predictive analytics; tax administration; data-driven approaches; risk assessment; ethical considerations; data privacy.

1. INTRODUCTION

Tax compliance remains a significant challenge for governments worldwide as they strive to maximize revenue collection and minimize losses caused by tax evasion and fraud (Luttmer & Singhal, 2014). The evolving complexity of financial transactions, coupled with the increasing sophistication of fraudulent schemes, necessitates the adoption of more advanced, dynamic, and efficient approaches to tax administration (Hassan, 2022). Traditionally, tax authorities have relied on methods such as audits, third-party reporting, and manual checks to ensure compliance and identify fraud. While these strategies have been effective in some contexts, they are increasingly insufficient to address the challenges posed by rapidly advancing technologies and novel economic activities (Mertens & Ravn, 2013; Olaniyi et al., 2023b; Olaoye et al., 2024b).

The advent of machine learning (ML) technologies offers a promising frontier in addressing tax non-compliance. With its ability to process large datasets, detect patterns, and flag potential fraudulent behaviors with unprecedented speed and accuracy, ML represents a substantial leap forward in the efficiency and effectiveness of tax collection systems (Donelson et al., 2022). ML not only enhances fraud detection but also provides tools for better risk management, predictive analytics, and resource optimization, allowing tax authorities to focus their efforts where they are most impactful (Olaniyi et al., 2023c; Olaniyi et al., 2023d). This paper seeks to examine the existing body of literature on the application of ML in tax compliance, focusing on its capacity to revolutionize traditional practices by augmenting detection mechanisms, improving operational efficiency, and optimizing revenue collection strategies (Crivelli & Gupta, 2018). By synthesizing existing research, this study highlights both the successes and challenges associated with ML implementation in tax systems (Olabanji et al., 2024; Wibowo, 2022).

The introduction sets the foundation for a comprehensive analysis of how machine learning technologies are currently deployed and their potential for future developments in tax administration (Oladoyinbo et al., 2024). Through a combination of literature review, case studies, and theoretical analysis, this paper provides a nuanced understanding of the transformative role of ML in global tax systems (Joseph et al., 2024; Olaniyi et al., 2024a; Olateju et al., 2024c). Subsequent sections delve into the theoretical underpinnings of ML in tax compliance, analyze its impact through real-world case studies, and explore the ethical, technical, and regulatory challenges that must be addressed to maximize its benefits (Hlomendlini, 2022; Sharma, 2016; Olaniyi et al., 2023a; Oreku, 2021). This exploration aims to equip policymakers, researchers, and tax administrators with insights into leveraging ML effectively to enhance compliance, mitigate fraud, and improve revenue mobilization in an increasingly complex economic landscape.

2. LITERATURE REVIEW

The integration of machine learning (ML) into tax compliance systems represents a transformative shift in how tax authorities address enforcement challenges and detect fraud (Cross et al., 2009).

This literature review synthesizes a diverse array of studies to chart the evolution of ML applications in tax administration, emphasizing theoretical advances and real-world implementations (Cao et al., 2022).

Early research in the field established the theoretical foundation for using ML to identify patterns indicative of non-compliance and fraudulent activities more effectively than traditional methods (Cross et al., 2009). Pioneering studies demonstrated the potential of basic predictive models, laying the groundwork for further exploration into advanced ML technologies (Cross et al., 2009). Since then, research has expanded dramatically, with recent studies exploring complex algorithms, including neural networks and deep learning, which offer greater accuracy and efficiency in detecting tax evasion (Cao et al., 2022).

The progression from simple predictive models to sophisticated machine learning applications has been well-documented in the literature (Donelson et al., 2022). Researchers such as Donelson et al. (2022) and Eva Andrés Aucejo (2024) have examined how newer, complex models enhance fraud detection. Comparative studies by Luttmer & Singhal (2014) highlight the improvements in compliance outcomes when ML tools are utilized, demonstrating significant advancements over traditional methods. These findings emphasize ML’s potential to transform tax administration by providing more effective tools for identifying non-compliance.

The practical application of ML in tax systems has been a focal point in recent studies (Joseph et al., 2024). Case studies by Joseph et al. (2024) and Olaniyi et al. (2024) document real-world implementations across various jurisdictions, outlining operational challenges and successes. Applied research by Haruna et al. (2023) and Iqbal (2023) explores specific use cases such as VAT compliance and income tax fraud detection, demonstrating ML’s adaptability across different tax contexts.

The literature also highlights the comparative effectiveness of ML over traditional tax compliance methods (Hassan, 2022). Studies by Hassan (2022) and Hlomendlini (2022) analyze the efficiency gains and cost reductions associated with ML, while economic analyses by Mertens & Ravn (2013) and Saez et al. (2012) underscore the economic benefits of ML, such as enhanced accuracy in tax collection and reduced administrative burdens. Alao et al. (2024) and Al-Hyari et al. (2023) further discuss the need for robust data governance frameworks, emphasizing that ML models heavily rely on high-quality, consistent data for accurate predictions.

Moreover, recent studies delve into data standardization across jurisdictions, with Beauvais et al. (2023) suggesting that international standards for tax data could significantly improve ML capabilities in tax administration. However, the implementation of ML in tax systems is not without challenges. Technical limitations, data quality issues, and high costs remain concerns, as discussed in case studies by the Enhancing Collection of Revenue and Expenditure Management Project (2022) and Erdoğan & Dirican (2022). Hlomendlini (2022) points out that ML adoption requires substantial investment and skilled personnel, creating barriers for many tax jurisdictions. Sithagu (2022) also raises ethical concerns, particularly regarding data privacy and algorithmic bias, which require careful consideration to maintain fairness and public trust.

Recent research highlights ML’s potential beyond fraud detection. Selesi-Aina et al. (2024) argue that ML can support broader tax functions, including real-time revenue forecasting and policy evaluation. Trawule et al. (2022) demonstrate that ML models provide insights into taxpayer behavior, enabling more targeted compliance strategies. These studies underscore ML’s adaptability across multiple tax administration areas, suggesting that its impact extends to data-driven decision-making.

Several researchers advocate a phased approach to ML implementation. Samuel-Okon et al. (2024) recommend using pilot programs to test ML solutions in smaller settings before scaling up, allowing authorities to identify potential issues early. This approach aligns with recommendations from Selesi-Aina et al. (2024), who emphasize the importance of ongoing model evaluation and updates to respond to evolving taxpayer behaviors and fraud tactics.

In conclusion, while ML offers powerful tools to improve tax compliance, its successful implementation requires addressing technical, ethical, and operational challenges. The literature underscores the need for robust data infrastructure, transparency, and phased deployment to maximize the benefits of ML. As ML technology evolves, it holds substantial promise for transforming tax administration, fostering greater efficiency, accuracy, and public trust.

3. EVOLUTION OF TAX COMPLIANCE STRATEGIES

The evolution of tax compliance strategies has been marked by significant advancements in technology and methodology. Historically, tax authorities relied heavily on manual processes and straightforward computational methods to ensure compliance and collect revenue. However, as economic systems have become more complex and globalized, these traditional methods have increasingly shown their limitations (Hassan, 2022).

Traditional Approaches: Traditional tax compliance strategies typically involved labor-intensive audits, manual record-keeping, and reliance on taxpayer honesty (Mertens & Ravn, 2013). These methods, while foundational, are not only resource-intensive but also limited in their scope and effectiveness, often failing to detect sophisticated tax evasion schemes (Saez et al., 2012).

Introduction of Technology: With the advent of computers and the internet, tax authorities began to adopt electronic filing and processing systems. These technologies allowed for faster data processing and easier access to taxpayer information, improving the efficiency of tax collection but still relying heavily on traditional verification methods (Luttmer & Singhal, 2014).

Integration of Advanced Analytics: The next phase in the evolution involved the integration of advanced analytics and data mining techniques. This era saw tax authorities starting to use statistical models to identify outliers and potential cases of non-compliance based on historical data (Cross et al., 2009). These methods provided a more proactive approach to compliance, allowing for targeted audits and better resource allocation (Crivelli & Gupta, 2018).

Implementation of Machine Learning: The latest and most transformative phase has been the adoption of machine learning technologies. ML models can analyze vast amounts of data quickly, learning from patterns and anomalies to predict potential fraud with greater accuracy than ever before (Donelson et al., 2022). This shift not only enhances the capability of tax authorities to detect and prevent fraud but also allows for a more nuanced understanding of taxpayer behavior, leading to more effective and less invasive compliance strategies (Joseph et al., 2024).

Comparative Effectiveness: The effectiveness of machine learning over traditional methods has been increasingly documented. Studies have shown that ML can reduce errors, lower costs, and increase the scope of compliance activities without additional human resources (Hlomendlini, 2022). Furthermore, the use of ML in tax compliance aligns with the growing need for digital and automated solutions in public administration, offering scalability and adaptability to various tax regimes (Iqbal, 2023).

4. MACHINE LEARNING IN TAX ADMINISTRATION

The adoption of machine learning (ML) in tax administration marks a critical shift towards more intelligent and data-driven approaches to enhancing compliance and combating tax evasion. This section explores how machine learning technologies are being implemented across various facets of tax administration, illustrating their impact through specific functionalities and outcomes.

Fundamentals of Machine Learning in Tax Systems: Machine learning utilizes algorithms to parse, learn from, and make decisions based on large datasets. In tax administration, ML is employed to analyze patterns from vast amounts of tax data, which can include everything from income declarations to transaction histories (Cao et al., 2022). This allows tax authorities to detect irregularities and potential fraud with a level of accuracy and speed that traditional methods cannot match (Donelson et al., 2022).

Key Applications of Machine Learning:

1. **Fraud Detection and Risk Assessment:** ML models are particularly effective at identifying anomalies that may indicate fraudulent activity. By learning from historical data, these models can flag unusual behavior for further investigation, significantly increasing the efficiency of audits (Joseph et al., 2024).
2. **Error Reduction:** Machine learning also helps in reducing errors in tax filings by

automatically detecting discrepancies in tax returns compared to historical patterns or common benchmarks (Haruna et al., 2023).

3. **Predictive Analytics:** ML enables tax authorities to forecast future trends in tax compliance and evasion, aiding in policy formulation and enforcement strategies (Olaniyi et al., 2024).

Implementation Challenges: While the benefits are substantial, the implementation of machine learning in tax administration is not without challenges. These include the need for significant investment in technology and training, concerns about data privacy and security, and the potential for bias in algorithmic decisions (Hassan, 2022). Furthermore, integrating ML systems with existing tax administration infrastructures often requires substantial customization and testing (Hlomendlini, 2022).

Case Studies:

Several successful implementations highlight the potential of ML in tax administration:

- **Income Tax Department:** A tax authority implemented an ML system to analyze and cross-reference income declarations with external data sources, leading to a significant increase in detection of underreported income (Iqbal, 2023).
- **VAT Compliance:** In another instance, machine learning was used to segment businesses based on risk profiles, allowing tax officials to focus their auditing efforts more effectively (Haruna et al., 2023).

Future Prospects: The future of machine learning in tax administration looks promising, with ongoing advancements in AI technology continuing to enhance the capabilities of tax authorities. As these systems become more sophisticated, they are expected to handle more complex tasks and provide greater insights into tax compliance behaviors (Donelson et al., 2022).

5. IMPACT OF MACHINE LEARNING ON TAX FRAUD DETECTION

The adoption of machine learning (ML) technologies has significantly enhanced the capacity of tax authorities to detect and prevent tax fraud. This section explores the specific impacts of ML on fraud detection, illustrating how these technologies improve accuracy, efficiency, and proactive enforcement in tax systems.

Enhanced Detection Capabilities: Machine learning algorithms excel at identifying complex patterns and anomalies in large datasets that would typically elude traditional detection methods. By continuously learning from new data, ML models can adapt to evolving fraudulent tactics more swiftly than static systems (Cao et al., 2022). This adaptability makes ML an indispensable tool in the modern tax administrator’s arsenal, particularly in detecting sophisticated evasion schemes that involve multiple data points and transactions (Donelson et al., 2022).

Automation and Efficiency: ML technologies automate the detection process, allowing for the analysis of vast quantities of data without the need for extensive human intervention. This automation significantly reduces the time required to identify potential fraud cases, enabling tax authorities to act more quickly and allocate resources more effectively (Joseph et al., 2024). Moreover, ML systems can operate 24/7, providing continuous monitoring and detection that enhances overall compliance coverage (Haruna et al., 2023).

Risk Assessment and Management: One of the key benefits of machine learning in tax fraud detection is its ability to assess and manage risk. ML models can rank taxpayers based on their likelihood of non-compliance or fraudulent behavior, focusing investigative resources on high-risk cases while minimizing unnecessary audits on compliant taxpayers (Olaniyi et al., 2024). This risk-based approach not only improves the efficiency of tax administrations but also ensures that compliance efforts are targeted and proportionate (Iqbal, 2023).

Challenges and Considerations: Despite these advantages, the implementation of ML in fraud detection comes with challenges. Data privacy concerns are paramount, as tax authorities must handle sensitive personal and financial information responsibly (Hassan, 2022). Additionally, there is a risk of biases in ML models that may lead to unfair treatment of certain taxpayer groups if not properly managed and audited (Hlomendlini, 2022).

Case Studies and Real-World Applications: Numerous case studies demonstrate the effective use of ML in detecting tax fraud. For instance, a European tax authority utilized ML models to identify unusual patterns in VAT submissions, resulting in the recovery of millions in unpaid taxes (Haruna et al., 2023). In another example, an ML system was deployed to cross-reference and analyze discrepancies between reported incomes and lifestyle indicators, significantly increasing the detection of underreported earnings (Iqbal, 2023).

Future Directions: As machine learning technology continues to evolve, its impact on tax fraud detection is expected to grow. Future developments are likely to include more sophisticated predictive analytics, enhanced data integration capabilities, and improved interpretability of ML decisions, which will further empower tax authorities to combat fraud effectively (Donelson et al., 2022).

6. ENHANCING REVENUE COLLECTION WITH MACHINE LEARNING

Machine learning (ML) has not only revolutionized the way tax authorities detect fraud but also significantly enhanced their ability to collect revenue more efficiently and effectively. This section examines the impact of ML on revenue collection processes, detailing how its capabilities lead to increased tax compliance and optimized revenue outcomes.

Increased Accuracy in Tax Assessments: Machine learning algorithms are adept at analyzing vast datasets to accurately assess tax liabilities. By processing data from multiple sources, ML models can provide a more comprehensive view of a taxpayer’s financial situation, leading to more precise tax assessments (Donelson et al., 2022). This increased accuracy helps ensure that all due taxes are collected, minimizing errors that could result in underpayment or overpayment (Joseph et al., 2024).

Automation of Collection Processes: The automation of tax collection processes through ML leads to significant improvements in operational efficiency. Automated systems can handle routine tasks, such as data entry and basic calculations, much faster than human workers, freeing up resources to focus on more complex compliance issues (Haruna et al., 2023). This shift not only speeds up the collection process but also reduces administrative costs, ultimately leading to a higher net revenue gain for tax authorities (Olaniyi et al., 2024).

Enhanced Compliance and Reduced Evasion: ML tools enable tax authorities to implement more effective compliance strategies by identifying patterns that indicate non-compliance or evasion (Cao et al., 2022). For instance, predictive analytics can be used to forecast potential defaulters based on historical data, allowing authorities to intervene proactively (Iqbal, 2023). Additionally, ML can enhance the enforcement of tax laws by pinpointing sectors or entities where evasion is most likely, thus directing enforcement efforts where they are most needed (Joseph et al., 2024).

Challenges in Implementation: Despite these benefits, implementing ML in revenue collection presents challenges. Significant investment in technology and training is required to fully leverage ML capabilities. There are also concerns about data security and the ethical use of data, especially regarding taxpayer privacy (Hassan, 2022). Moreover, the reliance on ML systems necessitates ongoing monitoring and updating to address any biases or errors that may arise (Hlomendlini, 2022).

Case Studies Demonstrating Success: Real-world applications have shown the potential of ML to boost revenue collection. For example, a pilot project in a North American tax authority used ML to optimize audit selections, which led to a 15% increase in revenue from audits compared to traditional methods (Haruna et al., 2023). Another case involved using ML to cross-analyze tax filings and external financial data, uncovering substantial amounts of unreported income (Iqbal, 2023).

Future Prospects: Looking ahead, the continued advancement of ML technologies promises even greater improvements in revenue collection. Innovations such as real-time data processing and more sophisticated anomaly detection algorithms are expected to further enhance the ability of tax authorities to collect taxes efficiently and fairly (Donelson et al., 2022).

7. CHALLENGES AND LIMITATIONS OF IMPLEMENTING MACHINE LEARNING

While machine learning (ML) offers transformative potential in tax administration, its implementation comes with significant challenges and limitations. This section explores the hurdles that tax authorities face in integrating ML into their systems, as well as the potential drawbacks of this technology.

Technical Challenges: One of the primary obstacles in adopting ML is the need for robust technical infrastructure. Tax authorities require advanced hardware and software to process and analyze large datasets effectively. Additionally, ML models require continuous updates and maintenance to remain effective, which can be resource-intensive (Donelson et al., 2022). The complexity of setting up and maintaining these systems often demands a high level of technical expertise, which may not be readily available within traditional tax administration staff (Joseph et al., 2024).

Data Quality and Availability: The effectiveness of ML is heavily dependent on the quality and quantity of data available. In many cases, tax authorities may struggle with incomplete, outdated, or inaccurate data, which can severely impact the performance of ML algorithms. Moreover, the integration of data from various sources often poses significant challenges, including issues with compatibility and data privacy (Hassan, 2022).

Privacy and Security Concerns: The use of ML in tax administration raises substantial concerns about data privacy and security. The processing of large volumes of personal and financial information increases the risk of data breaches, which can have serious repercussions for taxpayers' privacy rights. Ensuring the security of data and compliance with data protection regulations is a significant challenge for tax authorities implementing ML (Hlomendlini, 2022).

Ethical and Legal Issues: The deployment of ML systems must also navigate complex ethical and legal landscapes. Issues such as algorithmic bias can lead to unfair treatment of certain groups of taxpayers, potentially resulting in discriminatory practices. Tax authorities must ensure that ML models are transparent and accountable, and that decisions made by these systems can be explained and justified to the public (Hassan, 2022).

Resistance to Change: Implementing ML in tax systems often encounters resistance from within the organization and from the public. Employees may fear job displacement or distrust automated systems, while taxpayers may have concerns about the fairness and transparency of ML-driven decisions. Managing change and fostering trust are critical to the successful adoption of ML in tax administration (Haruna et al., 2023).

Cost of Implementation: The initial cost of implementing ML technology can be prohibitive, especially for smaller or resource-constrained tax authorities. The expenses associated with acquiring the necessary technology, training staff, and maintaining systems can deter many from adopting ML solutions (Iqbal, 2023).

While machine learning holds great promise for enhancing tax administration, overcoming these challenges is essential for its successful integration. Tax authorities must address these technical, ethical, legal, and operational issues to fully leverage the benefits of ML while minimizing its risks (Joseph et al., 2024). As the technology evolves, ongoing evaluation and adaptation will be crucial to ensuring that ML contributes positively to tax compliance efforts.

8. FUTURE DIRECTIONS AND RECOMMENDATIONS

As machine learning (ML) continues to advance, its potential to transform tax compliance and administration becomes increasingly evident. The rapid evolution of ML technologies provides opportunities to improve the accuracy, efficiency, and fairness of tax systems globally. This section examines key future directions for ML in tax systems and offers practical recommendations for its effective implementation to maximize benefits while addressing existing and emerging challenges.

Future Directions:

1. **Advanced Predictive Modeling:** Future developments in ML are expected to yield more sophisticated predictive models capable of forecasting non-compliance risks and identifying evolving fraud schemes with unprecedented precision. These models can help tax authorities preemptively tackle fraud, reducing revenue losses and improving compliance rates. Techniques like deep reinforcement learning will enhance predictive capabilities, allowing tax systems to adapt proactively to shifting taxpayer behaviors and fraud tactics (Cao et al., 2022; Donelson et al., 2022).
2. **Real-Time Data Processing:** Real-time ML-driven data processing is a promising frontier that could revolutionize compliance efforts. By monitoring transactions and filings as they occur, tax authorities can quickly detect irregularities and respond before significant revenue losses occur. This approach eliminates the delay inherent in retrospective audits, enabling

more dynamic and timely enforcement measures (Haruna et al., 2023).

3. **Enhanced Data Integration and Sharing:** ML applications in tax systems will benefit from increased integration of data across agencies and jurisdictions. Cross-border data sharing can improve the monitoring of global transactions, helping authorities detect tax evasion on an international scale. However, this requires robust protocols to ensure data security and privacy, particularly in compliance with global data protection regulations (Joseph et al., 2024; Hassan, 2022).
4. **Explainable and Transparent ML Models:** As ML adoption grows, the need for explainable and transparent models will become paramount. These models allow tax authorities to understand and justify ML-driven decisions, addressing concerns about accountability and fairness. Explainable AI can help build trust among taxpayers and stakeholders by ensuring that automated processes are interpretable and free from bias (Hlomendlini, 2022).
5. **Integration with Blockchain and Emerging Technologies:** Future ML systems could integrate with blockchain technology to enhance transparency, security, and traceability in tax transactions. Blockchain's immutable ledgers can complement ML's analytical capabilities, creating a comprehensive and trustworthy compliance framework. Additionally, combining ML with advancements in Internet of Things (IoT) and big data analytics could further improve monitoring and enforcement strategies.

Recommendations:

1. **Investment in Infrastructure and Expertise:** To fully leverage ML, tax authorities must invest in advanced technological infrastructure and develop a workforce skilled in ML operations. Partnerships with tech firms, academic institutions, and research organizations can provide access to cutting-edge technologies and expertise, accelerating ML adoption and innovation (Iqbal, 2023).
2. **Data Quality Enhancement:** High-quality data is fundamental to effective ML implementation. Tax authorities should refine their data collection methods, create centralized databases, and enforce rigorous data governance standards. Regular data audits and the adoption of uniform data protocols can ensure that ML models function optimally and produce reliable results (Olaniyi et al., 2024).
3. **Ethical and Regulatory Frameworks:** Establishing robust ethical guidelines and regulatory frameworks is essential to address concerns about data privacy, algorithmic fairness, and the potential for biased decision-making. Transparent practices in ML operations, including clear communication with taxpayers about how data is used, will foster trust and encourage compliance (Hassan, 2022; Hlomendlini, 2022).
4. **Gradual Implementation with Pilot Programs:** Tax authorities should adopt ML incrementally, starting with pilot programs to test models in controlled environments. This phased approach allows for the identification of potential issues and the refinement of ML systems before full-scale deployment, ensuring smoother integration and better outcomes (Joseph et al., 2024).
5. **Cross-Border Collaboration:** As tax evasion often involves international transactions, collaboration between tax authorities across jurisdictions is crucial. Shared standards, data-sharing agreements, and collaborative ML initiatives can strengthen global efforts to combat fraud and enhance compliance (Haruna et al., 2023).
6. **Continuous Monitoring and Model Updates:** ML models must be regularly evaluated and updated to reflect changes in taxpayer behavior, regulatory environments, and technological advancements. Establishing mechanisms for ongoing performance assessment and recalibration will ensure the sustained effectiveness of ML systems.

9. CONCLUSION

Machine learning (ML) is revolutionizing tax compliance and administration by providing powerful tools that enhance fraud detection, streamline revenue collection, and improve overall system efficiency. This literature review examines the evolution of tax compliance strategies, shedding light on the limitations of traditional approaches and emphasizing the transformative impact of ML (Cross et al., 2009; Cao et al., 2022). Through key studies and practical applications, it becomes clear that ML has significantly advanced the accuracy and speed of fraud detection, allowing tax authorities to proactively mitigate non-compliance risks and optimize revenue collection processes (Donelson et al., 2022; Joseph et al., 2024).

However, integrating ML into tax systems is not without its challenges. Issues related to data quality, technical infrastructure, privacy, and ethical considerations present significant hurdles for adoption (Hassan, 2022; Hlomendlini, 2022). To overcome these barriers, tax authorities must invest in modern technology, establish rigorous data governance practices, and develop ethical frameworks to ensure responsible use. Gradual implementation through pilot programs and enhanced international collaboration can further amplify ML's global impact on tax compliance (Haruna et al., 2023; Iqbal, 2023).

Looking to the future, the potential of ML in tax administration is immense. Advances in predictive analytics, real-time data processing, and explainable AI are expected to drive the development of more responsive, fair, and effective tax systems (Donelson et al., 2022). By addressing current challenges thoughtfully, tax authorities worldwide can foster a compliance environment that is efficient, transparent, and trusted by taxpayers. ML offers governments the opportunity to transform tax administration, reduce fraud, and maximize revenue collection while adapting to the complexities of modern economies. As ML technologies continue to evolve, their integration into tax systems could usher in a new era of innovation in public administration, paving the way for robust and adaptive tax systems that align with the needs of a globalized economic landscape (Joseph et al., 2024; Saez et al., 2012).

DISCLAIMER (ARTIFICIAL INTELLIGENCE)

Author(s) hereby declare that NO generative AI technologies such as Large Language Models (ChatGPT, COPILOT, etc.) and text-to-image generators have been used during the writing or editing of this manuscript.

COMPETING INTERESTS

Authors have declared that they have no known competing financial interests OR non-financial interests OR personal relationships that could have appeared to influence the work reported in this paper.

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https://www.sdiarticle5.com/review-history/126796