Machine Learning in Auditing: Problems, Solutions, Guidelines, Future Directions

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Abstract: In the modern and extremely dynamic business arena, auditing can be seen as the only way of getting financial information clarified, taking individuals who have that responsibility to account, and creating the impression of an honest player. The effectiveness of auditing is not just limited to risk mitigation approaches considering prevention of fraud, as it also strengthens the principles of legal compliance, market order, and economic stability in general. Several factors are propelling the auditing industry through a significant transformation at an increasingly fast rate, and these factors are big data and AI, of which machine learning (ML) is one of them. Traditional audits are made faster and more precision by ML through scrutinizing and interpreting enormous and complex data sets, such as detecting risk and anomaly violations and automatically generating reports. Yet, the auditing activities introduce ML into the auditing processes this creates another problem. These encompass issues of data quality and reliability, models transparency and interpretability for complex systems, risks of overfitting and underfitting, and also include security and moral considerations in the software and hardware regulations. On the other hand, there exists a cognate challenge of the auditors getting upskilled to effectively exploit these AI-driven technologies. This paper seeks to determine the problems of empirical evaluation of ML techniques and suggest possible solutions to maximize the efficiency and productivity of the auditing processes.

1 INTRODUCTION

Audit is one of the keystones of the present-day ever increasingly complicated and variable business environment, and audit should be seen as the foundation for pointing out the gaps in financial transparency and reliability.

Although it is the assessment of a company's performance measure, auditing is also important for fraud detection and prevention, internal control improvement, and risk management. The Implications of necessary auditing are apparent as a means of legal compliance, maintaining the market order, and the growth of the economy. In an age where information can be tantamount to money, auditing helps to maintain a public trust and assure the market standard.

The very apace at which technology is now manifesting itself, especially in data collection and artificial intelligence, has made machine learning (ML) emerge as a proverbial tool in a number of industries. From self-driving cars to product recommendation systems, ML technology has evolved so much that it can analyze and correlate data, which is fundamentally redefining the conventional practices. In the case of the auditing sector, which depends heavily on data correctness and speed, ML can save so much effort. Inside the audit process, the application of such techniques as anomaly detection, risk assessment, and automated report generation can help boost the efficiency and precision of audit outcomes significantly. A perfect example is ML; this technique can monitor financial transactions continuously in real time to detect any variations, provide predictive risk analysis, and generate a complete report about the audit, thus, saving human errors and increasing productivity (Hassan, 2023).

However, the implementation of Machine Learning in audits may not be without its difficulties, such as the ones associated with data quality, model transparency, overfitting and shifting characteristics, regulatory compliance, or the auditors' skills. A field

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of auditing that focuses on the implementation of machine learning identifies five issues: data quality and visualization, model interpretability and transparency, overfitting and generalization, regulatory compliance, and ethics, the skills and training gap among auditors. The section proposes the measures to improve data governance, model interpretability, overfitting control, compliance and ethical concerns, and auditor's technical skills all of which would contribute to the solution of these issues. Such methods are likely to contribute to the subsequent diligence of machine learning in auditing, resulting eventually in the growth of the quality and efficiency of audits. This article tries to deliver valuable findings and to present some recommendations of efficiently using ML for raising the level of audits' quality and providing compliance with the laws of compliance.

2 CHALLENGES

2.1 Data Accuracy and Precision

Another major feature concerning the auditors is the incomplete data that they get. The summary part of the report may be distorted in most cases when the transaction data, such as date, time, nature of transaction, cost of goods sold, etc., are revealed incompletely or inadequately. These areas inhibit machine learning from discerning anomalies, fraud and compliance violations; hence, the level of audit clutter cannot be trusted and lacks reassurance (Office of Inspector General, 2012). The utilization of machine learning on unsuitable and incomplete data sets will not only yield inaccurate insights, but also miss out on knowing the profound risks and anomalies the artificial intelligence should have been dealing with.

Discrepant data is one of the major difficulties confronting practitioners. Disparities in data entry systems, human mistake, and variable specificity of data sets could be the cause of drifted information between data source systems. Such differences can disrupt the engine of machine learning algorithms that form the basis of this whole idea, thereby provoking errant conclusions about risk assessment or wrong identification of mischief during the audit (Stefanov et al., 2012). For instance, labelling the same financial transactions originated from one source into different categories could mean that the machine will not be able to notice the patterns of fraud or error.

Additionally, machine learning is further complicated because of wrong data, like discrepancies in the transaction amounts or accounting transactions that are not in the right account. Such errors will result in a situation where the models are used to learn from the wrong information, and their outputs may not be useful inputs to even monetizing the said organization. Maintaining high quality and integrity of data becomes increasingly challenging but critical, particularly with businesses generating huge volumes of complex data.

In an environment where auditing becomes too demanding for the teams due to these data quality matters, the entire audit process may fail leading to serious mistakes in audit conclusions, and, moreover, it can result to failing to meet the compliance and regulatory requirements. Hence, the pillar that goes hand in hand with the capacity to utilize machine learning so as to improve audit accuracy, efficiency, and effectiveness is data quality and integrity (Stefanov, 2014). If these problems are not solved, many of the advantages of ML-driven practices will remain unexploited, and the overall audit result quality will be compromised.

2.2 ML Interpretation and Describe

An enormous difficulty to use machine learning in the auditing field is the issue of machine learning models transparency and interpretability. The advanced machine learning models, especially deep learning that are the most robust algorithms nowadays, tend to be "black boxes" thus having no knowledge of the way the decision-making is based on (Carvalho, Pereira, & Cardoso, 2019). These models utilize data processing as well as decision making systems that enable the algorithms to successfully do that, but the humans, including the auditors, cannot follow the internal procedures used for arriving at the decisions because such procedures are not clearly shown to them.

In auditing, this kind of uncertainly may be problematic since the auditors need to know the path of how decisions have been taken to achieve every conclusion. In finance, traditional auditing entails the following and logically verifying procedures and steps that are easy to understand. However, the process of machine learning has been found to be complex, and it is not easy to follow the road from input data to output decision, especially when there are deep neural networks with numerous layers in between. This complexity impedes auditors from interpreting the reasoning behind the model outputs to validate and attest audit findings which is one of the most important steps in the whole audit process.

Algorithmic systems' "black box" nature is usually taxing for an auditor because it becomes impossible to correctly illustrate the basis for unearthing the fraud or signs of suspicion. Having no specific understanding of how a model generates results presents an issue for auditors since this will make it quite hard to ensure the reliability and are correct these results (Knechel, 2013). This lack of clarity may weaken supposed confidence and truthful audit trails of the audit process, which the stakeholders rely on for the credibility of this profession.

2.3 Overfitting and Generalization

Overfitting is notoriously the biggest hazard that a machine learning model is in possession of, especially if this model is used to provide a complex task like auditing. In a nutshell, one type of the needless compliance with the training data appears to happen when the model captures the data set which it is already familiar with, namely capturing the general patterns beside the noises and anomalies present in that data set (Adler et al., 2018). Now, the model, which was otherwise perplexed by the training data, does almost perfectly on this new data set. So, it can't learn or maybe draw inferences from this data set which is not seen yet. The paraphrase of this is that the production of genuine data would be compromised by this situation of overfitting, and subsequently cannot be used in real time, which involves not only diverse but also varying data among different audit engagements.

In shapes of self-regulatory conflicts, overfitting to be found is more particular in the case of audit inspection. Auditors lag on ML algorithms and machines for identifying the fraudulent activities, estimating risk, and coming up with decisions based on historical and current financial data. Nonetheless, an overzealous working model that fails to see the randomness or specific pattern variants that are duplicates of the training data set can lead to false positives or false negatives. E.g., it might be found to incorrectly flag ordinary transactions to be fraudulent if they have the resemblance to the distortions of the training data, or miss out the real fraudulent transactions, which might appear to have the slight dissimilarities from the patterns the ML has learned.

Generalizing is made even more difficult by the fact that there are many different types of financial data. Undertaking of auditing purposely means dealing with diverse data from different clients, industry, or time, which all have differing characteristics. Striking a right balance between a model that is hyper-focused on one set of data and widely enveloping datasets can make the audit process reliable across various audit scenarios (Adler et al., 2018). This heterogeneity renders the machine learning models apart from being pre-programmed to learn from past information, they need to be pre-programmed to move freely within the real world and handle multiple and diverse situations.

2.4 Regulating Coherently and Ethically

Machine learning in the audit process introduces substantial challenges with respect to regulatory compliance, data privacy, security, and ethical dimensions. The advancement of the machine learning models, which are increasingly applied in the analysis of sensitive financial data and in making decisions that influence many stakeholders, imposes strict standards of ethics so that the regulation provides transparency, fairness, and customer satisfaction.

Another important aspect is the data privacy that is often prioritized and involve large volume of sensitive information with the clients, employees, and customers that is recorded on paper (Criado, Ferrer, & Such, 2021). The utilization of machine learning also becomes dependent on the ability to access and process the sensitive data; therefore, the sensitive data would be at risk of accidental data breaches and unauthorized access. People with data privacy in mind may not be comfortable with complying with the strict rules such as the GDPR in the EU of their personal data (Fasterling 2012). Machine Learning algorithms should thus employ techniques like pseudonymization, encryption, and additionally should have restricted access to the data by giving only the authorized personnel right of use.

Security is a fundamental element of strategy. Training models of machine learning demand the robust datasets that must be kept in a safe environment. It is within these datasets that probing and hacking may plague the system and thereby result to the undermining of the model outputs and therefore the audit results could be incorrect. Auditing entities are liable to build up resilient cybersecurity measures as the chief focus of thwarting any attacks by an organization and to guard their data infrastructure in a safe manner.

2.5 Education of Auditors and Skills

Riding on the border of progress in indexing machine learning into auditing is the gap in skills between the auditors. Historically, auditors defined themselves as financial analytics, risk assessors, and compliance auditors. However, there has been a simulation of AI in the current auditing system, and this has led to the addition of the technical form skills. These skills are understanding how machine learning models involve, interpreting their outcome, and detecting issues like encoding biases and model overfitting (Fasterling, 2012). Currently, many auditors are not adequately knowledgeable about these advanced tools, which can be a big deterrent to leveraging the utmost of these technologies, thus hampering the overall audit operation.

The speed at which new innovations in machine learning technologies are coming in increases the skills gap of those being trained and currently being tolerated for auditors. In conclusion, AI tools for measurement can create a lot of problems for an auditor who is not ready to meet a need for complex tasks include such as decision-making, risk management, and control. This situation brings about so many issues. Among the many other possibilities is the auditors not inspecting the machine learning models' outputs well and the assumptions and limitations inherent in the models; instead; they would take the model's outputs for granted and this might end with false audit conclusions.

The problems also involve the auditors who may have insufficient or deficient training; hence, they may have difficulties in interpreting the machine learning models' outputs. By contrast, the accounting principles that categorically specific each traditional audit procedures are not used in machine learning models. That is because it runs as a "black boxes," looking for the patterns in data that managers or auditors may not directly know (Cao, 2017). Non-specialized auditors in machine learning may have difficulties in forming audit findings that could be easily understandable, which is a counterbalance for why audit can be traced back and through.

3 SOLUTIONS

3.1 Data Accuracy and Consistency

Audit departments' data quality and integrity risks can be greatly minimized by introducing an effective data governance framework. The framework details how data is captured, stored, processed, and shared and it should be based on sound data management policies and standards. In the audit procedure, a data governance framework not only secures the consistency and reliability of these systems' performance but also prevents the occurrence of wrong judgments that may arise from the data quality issues. Besides, data stewards must frequently perform data quality assessments and audits to verify outdated, inaccurate, or incomplete record entries to ensure data accuracy. The data governance machine learning model has the potential to produce high-quality input data due to the internal data cleansing processes enforced by the audit departments, in turn enabling highly reliable and accurate audit results.

Before the auditors use the machine learning models, clean and prepare the data they receive using advanced techniques. It can entail the use of automating tools for detecting and correcting inconsistency, errors, and problems with outliers. For example, such algorithms can be applied during financial transaction audits to discover potential erroneous entries. Analyzing and processing lots of data before exposing them to machine learning models can eliminate influences from the data-related biases and inaccuracies. This clearly demonstrates, therefore, that the machine learning systems provide with accurate and reliable insights and results during audits, adding on the effectiveness of audits.

The range and detail of audits can be broadened by gathering data from different sources and integrating and verifying the collected information. This includes incorporating data from various in-house sectors such as finance, sales, and inventory systems, as well as external data consisting of market trends, economic indicators, and competitor information. By including such extensive data into the audit process, machine learning technology can analyze the vast patterns and trends and hence increase the precision of anomaly detection and risk assessment. Moreover, auditors ought to perform cross-validation on integrated data also because of its verification and consistency, which is an amplifier of the credibility of accounts.

3.2 Clarity and Explainability of Model

By integrating explainable AI like LIME or SHAP into the pre-audit process, it becomes easier for the auditors to scrutinize the developed system and obtain consistent outputs. These technologies are useful not only to explain how machine learning models reach their decisions, being probably able to verify and validate the correctness of outputs, and also to auditors to check that everything stays conformant. This clear connectedness is indispensable for the auditors to check whether the models facilitate the desired outcomes and subsequently precise their results to stakeholders.

Establish total model building documentation for machine learning used in audit systems. This document must contain the model's architecture, assumptions, input data, output data, and procedures on decision making. Furthermore, it is in the interest of trust and reliability to record model inputs and predictions in order to assist auditors in the improvement of audit results.

Leo should create machine learning models that are specifically designed for auditing, where simplicity is an absolute necessity. This may involve employing less complex approaches such as decision trees or linear regression, for example, which are straightforward as opposed to intricate deep networks. While these models have slightly lower predictability, they can still give you important explainable audits. This can be related to understanding the decisions made for compliance and accountability.

3.3 Model Overtraining and Auditors Broadening of Model Use

Employ k-fold cross-validation or other cross-validation methodologies to set the model's performance under different segments of the data to test how well it performs on new data. This methodology gives a better picture of underfitting by analyzing consistency in validating models across various data splits. The cross-validation method is, in fact, a quite rigorous method of checking the performance of the model, that is, its ability to generalize to unseen data. Since it is very crucial for the audit outcomes trustworthiness, it is widely used in practice.

Integrate L1 (Lasso) and L2 (Ridge) regression models for enforcing penalties on excessively complex ones, which are also more likely to overfit. Also, in tree-based classifiers, which are often important activity in auditing, pruning is applied to eradicate branches with unimportant impact or unreasonable numbers based on noise in training data. By means of these techniques, the model is simplified and thus it is possible to generalize it for the new data more easily.

All audit abusive scenarios should be considered by making audit training data convenient and representative of the different realities we see in our work. This can involve increasing the training dataset by creating synthetic data similar to that of infrequent or unusual cases. The model has been trained over a broad spectrum of examples, thereby it is more likely to be generalizing instead of building a model for a specific number of auditing contexts, with considerable risk posed by overfitting.

3.4 Legal Compliance and Ethics Regulations

Provide a range of audit-specific compliance professionals, such as data privacy experts and ethics officers, and ensure machines are appropriately integrated into auditing processes. The desired committees have the presence of lawyers, data privacy professionals, auditors, and ethicists. Theirs would be to develop policies and evaluate processes ensuring that the use of machine learning models abide by the relevant laws and regulations. Otherwise, individuals who abuse data in processing and/or usage without the right processes end up compromising the audit process. Thereby, it is unethical or not allowed according to the set standards.

The demand for a transparent and auditable system of machine learning in development and deployment should be established. This may require bringing the decision-making processes, data sources, and data-utilization methods of these models into clear light and publicly accessible. Transparency of all algorithms and data processing routines documentation not only develops confidence but also creates an audit journal to investigate data privacy and ethical problems.

The continuous assessment of ethical and compliance of machine learning systems in auditing ought to be done. These audits need to make sure that the models are up to standard with the latest regulatory requirements and ethical guidelines for auditing. Areas of concern may include data use, fairness of models, including "model bias" that make some of these decisions subject to scrutiny, and identification of possible threats. Regular audits contribute to the immediate diagnosis of any identified problems without fuelling severe consequences. This, therefore, is used to confirm that the use of machine learning in auditing is always compliant and textually sound.

3.5 Knowledge and Experience of Apprentices

Establish specific training programs on machine learning, which are mainly oriented towards auditing. This part should include basic machine learning concepts, data analysis methods, as well as practical functionalities such as anomaly detection, risks assessment, and trend analysis in audit data. Real-life scenarios may be carried through in case studies that can exemplify how machine learning can be of benefit in the auditor's day-be-day job. In this regard, the fact that they will have practical experience in the field does not only help these auditors to grasp machine learning concepts but also to be able to use them in their works.

Generate and launch audit management tools and systems that bring machine learning capabilities, thus allowing the auditors to use these technologies. This tool can reduce the burden on the auditors by automating data processing, anomaly detection, and risk identification tasks, thereby letting auditors to put maximum emphasis on their judgment and decision making. In this, the tools ought to have intuitive user interfaces and offer detailed assistance and support to help the auditors sooner adapt themselves to the technologies and manage to acquire mastery of the new techniques.

Get a machine learning support team in-house dedicated to auditors or utilize the external machine learning consultants to provide assistance with complicated technical problems. This team can act as a helpdesk to help auditors with technical problems regarding the application of machine learning or with complex data analysis tasks. Consequently, auditors will be able to internalize and apply the machine learning techniques while assuring the correctness and quality of the audit procedures.

4 BEST PRACTICES

4.1 Continuous Learning and Development

To give auditors a chance to get acquainted with the possibilities of machine learning tools, companies should regularly hold training events to introduce the fundamentals of ML, recent advances, and their use in auditing. These training courses can solve practical problems. For example, auditors can receive practical case study examples and will be able to apply what was learned in the training room to the real world that awaits this concept in its preparation. This practical method provides that auditors comprehend the concepts of machine learning and getting skills to use them by auditors accordingly.

4.2 Form Cross-functional Teams

It is better to involve scientists, audit experts, and IT professional within interdisciplinary teams to audit those machine learning models. These groups may work together to obtain and fine-tune models that are scientific yet still meet the requirements of auditing. While working in a teamwork manner, the audit professionals tend to get a better insight into the audit specifications and hence design appropriate technical solutions. Such an inclusive approach always ensures that the developed models are not only technically good but are also practically important for auditing.

4.3 Develop Agile Development Methodologies for Businesses

Adopting Agile development techniques is the best way to apply machine learning in auditing. This approach lets teams build, analyse, and retest their models quickly, uniquely modifying them based on the feedback they get. Agile methodology supports the flexibility and correctness of those models and aids quick detection of possible disruptions that could arise and cause serious losses. Up to date, by using iterative development, organization can gradually improve design of their models according to the changes in audits processes.

4.4 Improve Data Management and Governance

The quality of data and its management bore keen importance for the use of machine learning is a successful audit. We must come up with a data management and governance model that addresses these critical dimensions to enhance the data reliability, validity, and completeness. The entire process of data generation, storing, running, and sharing should obey strict standards, protocols, and guidelines to help the machine learning applications along with the efficient and reliable ones. As a process, data governance not only improves the audit quality but also allows for compliance with rules governing data protection and privacy.

4.5 Model Validation and Continual Improvement

Application of the regular model validation and evaluation methods is a primal stage keeping the quality in check of the machine learning models as well as the accuracy of the audit results. Through ongoing observation and feedback loops, organizations become capable of quickly spotting aberrations in the models, which inevitably leads to their consistent and optimal performance. Regular validation keeps the models in line with auditing standards and practices upgrade, making them the tool which remain effective in long term.

5 FUTURE DIRECTIONS

5.1 Broadening the Field of Interpretability and Transparency

Interpretability as well as transparency are both critical in machine learning of audits as the auditors need to comprehend and explain the reasoning process of machine learning models to ensure their fair and accurate results. Although complex models, such as deep learning, achieve the aforementioned results through their black-box nature, full knowledge of model processes is complex and difficult for auditors. The next step of building interpretable ML methods should become the key goal of modern research, both in academic and industrial environments. In addition to the current models like LIME (Local Interpretable Model-agnostic Explanations) and SHAP (SHapley Additive exPlanations), the other important aspect is to see how we can leverage the neural networks and deep learning models and make them more transparent. There're different ways to achieve that, these include putting forward user-friendly model architectures or introducing interpretability as an objective function during model development. Implementing such techniques would serve not only in the proper understanding of the output of the models but also the increasing of the credibility of theses so that the audit findings can be relied on and accepted.

5.2 Integration with Multimodal Data

Auditing focus relies too much on financial dimensions in reality and does not harness the opportunity of unstructured data. Next-generation audit technologies must be multifunctional, hence should be able to handle and combine multiple data types, such as text, images, and audio. This is made possible by multimodal machine learning models, which allow the auditors to observe and learn from studying data from various scope. One option could be to use NLP techniques to perform an analysis of the internal communication records (such as email or chat logs) that are stored within a company to help out in the identification of fraud or any other compliance violations. On the contrary, computer vision techniques can be used to reveal discrepancies and anomalies that might be present in scanned contracts and documents. It will vastly improve the uniformity and correctness of the audit process to consolidate into one the complementary types of data that insightfully goes together in audit results.

5.3 Live Auditing and Continuous Monitoring

With the operations environment of businesses becoming much more sophisticated and evolving rapidly, instant auditing with constant surveillance seems to be the trend. Consequently, such a viewpoint requires machine learning models to ingest and comprehend data streams from a multitude of sources, with the goal of immediate response to anomalies and risks, which may appear at the same time. The resultant effect is that such real-time data stream processing algorithms and systems architectures that are equipped with the ability to continuously monitor business processes and detect anomalies based on an established criterion or model will be developed. Taking note of the potential for financial crimes at that moment, real-time tracking of financial transactions and account activity could provide notice about the existence of any possible fraud or financial crime and prompt the undertaking of corrective actions. For such an accomplishment, studies would need to be extended to not only the development of ML models, but also resource management that involves computing, communication, and system integration.

5.4 Firming up Ethics and Regulatory Compliance

Machine learning use in auditing undoubtedly brings the challenges in data privacy and ethics with it. Future research should concentrate on how to make the integration of data utilization and analysis not only effectively but also maintaining the data privacy. The algorithms of privacy maintenance, for instance, differential privacy, can lessen the chance of disclosure of sensitive information about some personal parts during the processing of the data. Additionally, the development of data protection regulations such as GDPR and CCPA pushes organizations into designing compliance algorithms to make sure that models' operations do adhere with laws of the land. Another central issue is algorithmic bias; machine learning models may unconsciously capture the biases that were present in the training data. Thus, a future research focus should be on algorithms which are developed to detect and minimize bias, thus ensuring models make impartial and fair decisions. The features will not only increase the acceptability of models in the legal realm and social but also help in enhancing their applicability in the auditing field.

6 CONCLUSIONS

In a business environment that is so varied and competitive, auditing is still valuable in terms of book-keeping, adherence to laws, and financial system stability. The inclusion of machine learning (ML) has brought with it a slew of benefits in the form of improved accuracy and processing times in audit routines, such as fraud detection, risk profiling, and automated auditing reports, to name a few. However, despite the convenience, the application of ML in the area of auditing still has some issues that need to be addressed. These problems are features of data quality, model transparency, overfitting, and regulatory compliance. Also, ethical concerns in combination such as data ownership and fairness of algorithms have to be dealt with prudence. Instead of looking for the benefits of implementing ML in auditing, data governance frameworks should be reinforced, model interpretability improved, and training provided for auditors. Tackling these problems will enable the fair usage of ML in auditing, which is bettering audit quality in addition to keeping the right ethical and legality standards.

REFERENCES

Adler, P., et al. (2018). Auditing black-box models for indirect influence. Knowledge and Information Systems, 54, 95-122.

Cao, L. (2017). Data science: a comprehensive overview. ACM Computing Surveys (CSUR), 50(3), 1-42.

Carvalho, D. V., et al. (2019). Machine learning interpretability: A survey on methods and metrics. Electronics, 8(8), 832.

Criado, N., et al. (2021). Attesting Digital Discrimination Using Norms.

Fasterling, B. (2012). Development of norms through compliance disclosure. Journal of Business Ethics, 106, 73-87.

Hassan, G. M. (2023). Influence Of Corporate Governance Practises on Service Delivery Among County Governments In Kenya. KCA University,

Ilori, O., et al. (2024). Advanced data analytics in internal audits: A conceptual framework for comprehensive risk assessment and fraud detection. Finance & Accounting Research Journal, 6(6), 931-952.

Karpoff, J. M., et al. (2012). A critical analysis of databases used in financial misconduct research. Mays Business School Research Paper, 73(2012), 2012-2011.

Knechel, W. R. (2013). Do auditing standards matter? Current Issues in Auditing, 7(2), A1-A16.

Odeyemi, O., et al. (2024). The role of AI in transforming auditing practices: A global perspective review. World Journal of Advanced Research and Reviews, 21(2), 359-370.

Stefanov, E., et al. (2012) "Iris." Proceedings of the 28th Annual Computer Security Applications Conference on - ACSAC '12.

Song, Q. C., et al. (2021). Making sense of model generalizability: A tutorial on cross-validation in R and Shiny. Advances in Methods and Practices in Psychological Science, 4(1), 2515245920947067.