Open Access Research Journal of
Multidisciplinary Studies
Journals home page: https://oarjpublication/journals/oarjms/
ISSN: 2783-0268 (Online)

OARJ OPEN ACCESS RESEARCH JOURNALS

(REVIEW ARTICLE)

Check for updates

Machine learning in budget forecasting for corporate finance: A conceptual model for improving financial planning

Jeremiah Olamijuwon [1,*] and Stephane Jean Christophe Zouo [2]

[1] *Etihuku Pty Ltd, Midrand, Gauteng, South Africa.*
[2] *Department of Business Administration, Texas A&M University Commerce, Texas, USA.*

Open Access Research Journal of Multidisciplinary Studies, 2024, 08(02), 032–040

Publication history: Received on 23 September 2024; revised on 01 November 2024; accepted on 04 November 2024

Article DOI: https://doi.org/10.53022/oarjms.2024.8.2.0061

Abstract

This paper explores the transformative potential of machine learning (ML) in budget forecasting within corporate finance. It begins with an examination of the importance of accurate budget forecasting for financial planning and the limitations of traditional methods. Theoretical foundations of ML are then discussed, highlighting relevant techniques such as regression, time series analysis, and neural networks. A conceptual model for ML-driven budget forecasting is proposed, detailing its components, architecture, and integration into financial planning processes. The paper also addresses the expected benefits, including improved accuracy and efficiency, alongside the challenges such as data quality, ethical considerations, and organizational barriers. By navigating these challenges through robust data governance, ethical practices, and strategic implementation, organizations can significantly enhance their budget forecasting processes, leading to better financial outcomes and strategic decision-making.

Keywords: Machine Learning; Budget Forecasting; Corporate Finance; Financial Planning; Data Quality; Ethical Considerations

1. Introduction

Budget forecasting is a cornerstone of corporate financial planning, providing a roadmap for businesses to navigate their financial futures. It involves predicting future revenues, expenses, and other financial metrics based on historical data, current market conditions, and anticipated business activities. Accurate budget forecasting is crucial for several reasons. Firstly, it helps organizations allocate resources efficiently, ensuring that funds are available for critical operations and investments (Nguyen, Sermpinis, & Stasinakis, 2023). Secondly, it enables businesses to identify potential financial shortfalls and take proactive measures to mitigate risks. Thirdly, reliable forecasts support strategic decision-making by providing insights into future financial performance, helping executives set realistic goals and priorities. Effective budget forecasting is vital for maintaining financial stability, driving growth, and achieving long-term business objectives (de Zarzà, de Curtò, Roig, & Calafate, 2023).

In recent years, machine learning (ML) has emerged as a transformative force in various industries, including finance. Machine learning, a subset of artificial intelligence (AI), involves the use of algorithms and statistical models to analyze and interpret complex data patterns, enabling systems to learn and make predictions or decisions without explicit programming. In the financial sector, ML applications are diverse and far-reaching (Biju, Thomas, & Thasneem, 2024). They include fraud detection, where algorithms analyze transaction data to identify suspicious activities; credit scoring, where models assess the creditworthiness of individuals and businesses; algorithmic trading, which involves automated trading strategies based on market data analysis; and customer service, where chatbots and virtual assistants provide personalized financial advice (Mahalakshmi et al., 2022).

* Corresponding author: Olugbenga Jeremiah Olamijuwon

Budget forecasting is one of the most promising applications of machine learning in finance. Traditional forecasting methods, such as linear regression and moving averages, often fall short in handling the complexities and dynamics of financial data. Machine learning, on the other hand, excels in processing large volumes of data, capturing intricate patterns, and adapting to changing conditions. By leveraging ML techniques, businesses can enhance the accuracy and reliability of their budget forecasts, leading to better financial planning and decision-making (Masini, Medeiros, & Mendes, 2023).

The primary purpose of this paper is to propose a conceptual model for improving budget forecasting in corporate finance through the application of machine learning techniques. As businesses operate in increasingly volatile and competitive environments, the need for precise and adaptable financial forecasting tools has never been greater. This paper aims to address this need by exploring how machine learning can revolutionize budget forecasting, providing a more robust and sophisticated approach compared to traditional methods.

The objectives of the paper are threefold. First, it seeks to provide a comprehensive overview of the theoretical foundations of machine learning as they pertain to financial forecasting. This includes an examination of various ML algorithms and their relevance to budget forecasting tasks. Second, the paper aims to introduce a conceptual model that integrates machine learning techniques into the budget forecasting process. This model will outline the key components and architecture necessary for effective implementation. Third, the paper will discuss the potential challenges and considerations associated with adopting machine learning for budget forecasting, including data quality issues, ethical considerations, and organizational barriers. By addressing these objectives, the paper aims to offer valuable insights and practical guidance for businesses looking to enhance their financial planning through machine learning.

2. Theoretical Foundations of Machine Learning in Finance

2.1. Overview of Machine Learning Techniques Relevant to Budget Forecasting

Machine learning (ML) has revolutionized numerous fields, including finance, by providing advanced data analysis and prediction tools. In budget forecasting, several ML techniques stand out due to their ability to handle complex datasets and generate accurate predictions. These techniques include regression analysis, time series forecasting, and neural networks, each offering unique strengths for different aspects of financial forecasting (Sen, Sen, & Dutta, 2022).

Regression analysis, a fundamental statistical method, forms the basis of many machine learning models. In finance, regression models can predict future financial outcomes by analyzing the relationships between various independent variables and the dependent variable, such as revenue or expenses. Time series forecasting, another critical ML technique, involves analyzing historical data points to predict future values (Irfan, Elhoseny, Kassim, & Metawa, 2023). This method is particularly useful for budget forecasting as it accounts for trends, seasonal patterns, and cyclical variations in financial data. Neural networks, inspired by the human brain's structure and function, are highly versatile and capable of capturing complex, non-linear relationships in data. These models are particularly effective in scenarios where traditional methods fall short, providing robust predictions even in the presence of noisy or incomplete data (Wasserbacher & Spindler, 2022).

2.2. Key Concepts and Algorithms

Within the scope of regression analysis, various algorithms are employed to enhance the predictive power of models. Linear regression, one of the simplest forms, predicts outcomes based on the linear relationship between input variables. Multiple linear regression extends this concept by considering multiple factors simultaneously, improving accuracy in complex financial environments. Beyond linear regression, logistic regression is used for binary classification problems, such as predicting the likelihood of financial events occurring or not (Lai & Dzombak, 2020).

Time series analysis encompasses several sophisticated techniques tailored to handle sequential data. The Autoregressive Integrated Moving Average (ARIMA) model is widely used for its ability to capture autocorrelations in time series data, making it suitable for financial forecasting. The Seasonal Decomposition of Time Series (STL) is another powerful method that decomposes a time series into trend, seasonal, and residual components, providing insights into underlying patterns and improving forecast accuracy (Schaffer, Dobbins, & Pearson, 2021).

Neural networks, particularly deep learning models, have gained prominence due to their ability to process large datasets with high-dimensional features. Feedforward neural networks (FNNs) and recurrent neural networks (RNNs) are two primary types used in financial forecasting (Latif et al., 2020). FNNs are suitable for static data prediction, while RNNs, especially Long Short-Term Memory (LSTM) networks, excel in capturing temporal dependencies in sequential data, making them ideal for time series forecasting. LSTMs can remember long-term dependencies, which is crucial for accurate financial predictions that depend on past data trends (Michailidis, Michailidis, Gkelios, & Kosmatopoulos, 2024).

2.3. Advantages of Using Machine Learning Over Traditional Forecasting Methods

Machine learning offers several significant advantages over traditional forecasting methods, making it an invaluable tool for budget forecasting in corporate finance. Firstly, ML models can handle large volumes of data from diverse sources, enabling more comprehensive analyses. Traditional methods often struggle with high-dimensional datasets, leading to oversimplified models and less accurate predictions. In contrast, ML algorithms thrive in data-rich environments, uncovering hidden patterns and relationships that traditional models might miss (Birim, Kazancoglu, Mangla, Kahraman, & Kazancoglu, 2024).

Secondly, ML techniques can capture non-linear relationships and interactions between variables. Financial data is inherently complex and influenced by numerous factors, many of which interact in non-linear ways. Traditional linear models, while useful, cannot fully capture these intricacies. Machine learning models, particularly neural networks, can model these complex relationships, providing more accurate and reliable forecasts (Venkataramanan, Sadhu, Gudala, & Reddy, 2024).

Thirdly, ML models are highly adaptable and can improve over time as they are exposed to new data. This adaptive capability is crucial in the dynamic financial environment, where conditions can change rapidly. Traditional models often require manual recalibration and updating, which can be time-consuming and prone to human error. Machine learning models, on the other hand, can continuously learn and adjust to new data, ensuring that forecasts remain relevant and accurate (Chan et al., 2022).

Moreover, machine learning enhances predictive accuracy through ensemble methods, which combine multiple models to improve overall performance. Techniques such as bagging, boosting, and stacking integrate the strengths of individual models, reducing errors and increasing robustness. For instance, Random Forests and Gradient Boosting Machines (GBMs) are popular ensemble methods that have shown superior performance in various financial forecasting tasks (Miceli, Hagen, Riccardi, Sotti, & Settembre-Blundo, 2021).

Another critical advantage is the ability of ML models to handle unstructured data, such as text from financial reports, news articles, and social media posts. Natural Language Processing (NLP) techniques allow ML models to extract valuable insights from these sources, enriching the data available for forecasting. This capability is particularly useful for sentiment analysis, where the model assesses market sentiment and its potential impact on financial performance (Kang, Cai, Tan, Huang, & Liu, 2020). Furthermore, ML models can be integrated with advanced simulation techniques to provide scenario analysis and stress testing. These simulations allow businesses to explore various hypothetical scenarios and assess their potential impact on financial outcomes. By incorporating machine learning into these processes, organizations can gain deeper insights into potential risks and opportunities, enhancing their strategic planning capabilities (Rane, Choudhary, & Rane, 2024).

3. Conceptual Model for Machine Learning-Driven Budget Forecasting

3.1. Description of the Proposed Conceptual Model

The proposed conceptual model for machine learning-driven budget forecasting aims to revolutionize the traditional approaches to financial planning by integrating advanced machine learning techniques. This model is designed to enhance budget forecasts' accuracy, efficiency, and adaptability, addressing the limitations of conventional methods that often struggle with handling complex and dynamic financial data. The core idea behind this model is to leverage the predictive power of machine learning algorithms to analyze vast amounts of historical and real-time data, identify patterns, and generate reliable forecasts that can support strategic decision-making in corporate finance.

The model operates on the principle that financial data, while complex and multifaceted, contains underlying patterns and trends that machine learning algorithms can detect and exploit. By incorporating various machine learning techniques, the model can process large datasets, account for multiple variables, and adjust to new information continuously. This adaptability is crucial for maintaining the relevance and accuracy of budget forecasts in a rapidly changing business environment.

3.2. Components and Architecture of the Model

The proposed model consists of several key components, each playing a vital role in the forecasting process:

- Data Collection and Preprocessing: The foundation of the model is built on high-quality data. This component involves gathering data from various sources, including financial statements, market trends, economic indicators, and internal business metrics. The data is then cleaned, normalized, and transformed into a suitable format for analysis. Preprocessing steps such as handling missing values, outlier detection, and feature engineering are critical to ensure the integrity and usability of the data.
- Feature Selection and Extraction: Identifying the most relevant features is essential for building effective machine learning models. This component involves selecting and extracting key variables that significantly impact budget forecasts. Techniques such as Principal Component Analysis (PCA) and domain expertise are used to reduce dimensionality and enhance the model's performance by focusing on the most influential factors.
- Model Selection and Training: This is the heart of the conceptual model, where various machine learning algorithms are evaluated and selected based on their suitability for the forecasting task. Algorithms such as linear regression, time series models (e.g., ARIMA, SARIMA), and neural networks (e.g., LSTM, GRU) are trained on historical data. The training process involves optimizing model parameters to minimize forecasting errors and improve predictive accuracy.
- Model Validation and Testing: To ensure the reliability of the forecasts, the model undergoes rigorous validation and testing. Techniques such as cross-validation and backtesting are employed to assess the model's performance on unseen data. This step helps fine-tune the model, address overfitting, and ensure that the forecasts are generalizable to real-world scenarios.
- Forecast Generation and Analysis: The model is deployed to generate budget forecasts once validated. This component involves running the trained model on current and projected data to produce forecasts for various financial metrics. The forecasts are then analyzed to identify trends, potential risks, and opportunities, providing valuable insights for financial planning.
- Visualization and Reporting: Effective communication of the forecasts is crucial for informed decision-making. This component includes creating visualizations such as charts, graphs, and dashboards to present the forecast results in a comprehensible and actionable format. Automated reporting tools are integrated to deliver timely updates to stakeholders.

3.3. Integration of Machine Learning Techniques into Financial Planning Processes

Integrating machine learning techniques into financial planning processes involves several strategic steps to ensure seamless adoption and maximum impact. The first step is to establish a robust data infrastructure that supports collecting, storing, and processing large datasets. This includes implementing data warehouses, cloud storage solutions, and data integration platforms that facilitate easy access to financial data from diverse sources.

Next, organizations need to foster a data-driven culture by encouraging collaboration between finance professionals and data scientists. This interdisciplinary approach ensures that domain expertise informs the model development process, leading to more accurate and contextually relevant forecasts. Training programs and workshops can help finance teams understand the capabilities and limitations of machine learning, promoting their active involvement in the implementation process.

Furthermore, developing a feedback loop that continuously monitors the performance of the machine-learning models is essential. By regularly updating the models with new data and evaluating their accuracy, organizations can ensure that the forecasts remain current and reflective of the latest market conditions. This iterative approach allows for the continuous improvement of the forecasting process, adapting to changing business environments and emerging trends (Okoduwa et al., 2024; Udegbe, Ebulue, Ebulue, & Ekesiobi, 2024c).

Lastly, integrating machine learning into financial planning requires addressing ethical considerations and ensuring data privacy and security. Establishing governance frameworks defining data usage policies, compliance requirements, and ethical guidelines is critical to maintaining trust and integrity in forecasting (Udegbe, Ebulue, Ebulue, & Ekesiobi, 2024b).

3.4. Expected Benefits and Improvements in Accuracy and Efficiency

The integration of machine learning-driven budget forecasting offers numerous benefits, significantly enhancing the accuracy and efficiency of financial planning processes. One of the primary advantages is the improved accuracy of forecasts. Machine learning algorithms can analyze complex datasets and identify patterns that traditional methods often miss, resulting in more precise and reliable predictions. This heightened accuracy enables organizations to make better-informed decisions, reducing financial risks and enhancing strategic planning (Yang & Shami, 2022).

Another key benefit is the efficiency gained through automation. Machine learning models can process vast amounts of data much faster than manual methods, significantly reducing the time required to generate forecasts. This efficiency allows finance teams to focus on higher-value tasks, such as strategic analysis and decision-making, rather than being bogged down by time-consuming data processing and manual calculations (Ogugua, Okongwu, Akomolafe, Anyanwu, & Daraojimba, 2024; Udegbe, Ebulue, Ebulue, & Ekesiobi, 2024a).

Additionally, the adaptability of machine learning models ensures that forecasts remain relevant in dynamic environments. Unlike static traditional models, machine learning algorithms can continuously learn from new data and adjust their predictions accordingly. This flexibility is crucial for businesses operating in volatile markets, where conditions can change rapidly and unpredictably (Taye, 2023). Furthermore, the use of machine learning in budget forecasting enhances the granularity and depth of financial insights. By analyzing multiple variables and their interactions, machine learning models can provide a more comprehensive view of financial performance, identifying emerging trends and potential risks that may not be apparent through traditional methods. This deeper understanding enables organizations to proactively address challenges and capitalize on opportunities, driving better financial outcomes (Abdulla, Demirci, & Ozdemir, 2022).

4. Challenges and Considerations

4.1. Potential Challenges in Implementing Machine Learning for Budget Forecasting

Implementing machine learning (ML) for budget forecasting in corporate finance is a promising endeavor, yet it presents several challenges that organizations must navigate to realize its full potential. These challenges span technical, organizational, and ethical domains, each requiring thoughtful consideration and strategic management.

One of the primary challenges is the complexity of machine learning algorithms. These models often require significant expertise to develop, tune, and interpret. Unlike traditional statistical methods, ML models involve sophisticated computations and parameters that necessitate specialized data science and machine learning knowledge. This complexity can be a barrier for finance teams that are accustomed to more straightforward analytical tools, leading to a steep learning curve and potential resistance to adoption (Rudin et al., 2022).

Another challenge is the integration of ML models into existing financial systems and workflows. Financial planning and analysis (FP&A) teams rely on established processes and tools like spreadsheets and enterprise resource planning (ERP) systems. Incorporating ML models into these workflows can be disruptive and may require substantial changes in how data is processed, analyzed, and reported. This integration necessitates careful planning and collaboration between data scientists, IT professionals, and finance teams to ensure a smooth transition (Pichler & Hartig, 2023).

4.2. Data Quality and Availability Issues

Data is the lifeblood of machine learning models, and the quality and availability of data are critical factors that influence the accuracy and reliability of budget forecasts. One of the significant challenges in this regard is ensuring that the data used to train ML models is clean, consistent, and comprehensive. Financial data can be messy, with issues such as missing values, outliers, and inconsistencies that can adversely affect model performance (Zhong et al., 2021).

Moreover, data availability can be a limiting factor. Machine learning models thrive on large datasets to learn patterns and make accurate predictions. However, historical financial data may be incomplete, siloed, or inaccessible in many organizations. Data fragmentation across different departments and systems can hinder aggregating and utilizing comprehensive datasets for training ML models. Addressing these issues requires robust data governance practices, including data cleansing, standardization, and integration, to ensure that the data feeding into the ML models is of high quality (Hardt & Recht, 2022).

4.3. Ethical Considerations and Bias in Machine Learning Models

The ethical implications of deploying machine learning models in budget forecasting cannot be overlooked. One of the primary ethical concerns is the potential for bias in ML models. Bias can arise from various sources, including biased training data, algorithmic bias, and the subjective decisions made during model development. Suppose the data used to train the models reflects historical biases or systemic inequalities. In that case, the predictions generated by these models may perpetuate or even exacerbate these biases (Kim, Park, & Suh, 2020).

For example, if a company's historical budget allocation data reflects discriminatory practices, an ML model trained on this data might continue to allocate resources in a biased manner. This could result in unfair financial planning decisions that disadvantage certain departments or projects. To mitigate these risks, it is essential to implement rigorous bias detection and mitigation strategies, such as using diverse and representative datasets, applying fairness constraints in model training, and conducting regular audits of model outputs to ensure fairness and equity (Belenguer, 2022).

Additionally, using machine learning in financial decision-making raises concerns about transparency and accountability. ML models, particularly complex ones like neural networks, can be opaque, making it difficult to understand how they arrive at their predictions. This "black box" nature of ML can be problematic in corporate finance, where stakeholders need to trust and verify the models' outputs. Ensuring transparency through explainable AI techniques and maintaining accountability through governance frameworks are critical steps to address these ethical considerations (Rane et al., 2024).

4.4. Organizational and Technical Barriers

Beyond technical challenges, significant organizational barriers exist to implementing machine learning in budget forecasting. One of the most prominent barriers is the resistance to change within the organization. Finance professionals may be skeptical of adopting new technologies that disrupt traditional processes and require them to learn new skills. This resistance can be mitigated through effective change management strategies, including training programs, workshops, and clear communication about the benefits and goals of the ML implementation (Schmidt, Riley, & Swanson Church, 2020).

Another organizational barrier is the alignment of objectives and priorities between different stakeholders. Successful implementation of ML models for budget forecasting requires collaboration between finance, IT, data science, and executive leadership. Each of these groups may have different priorities and perspectives, leading to potential conflicts and misalignment. Establishing cross-functional teams and fostering a culture of collaboration and shared goals can help bridge these gaps and ensure a unified approach to ML adoption (Machireddy, Rachakatla, & Ravichandran, 2021).

Technical barriers also pose significant challenges. Implementing ML models requires robust IT infrastructure, including powerful computational resources, scalable storage solutions, and secure data management systems. Many organizations may lack the necessary infrastructure to support large-scale ML deployments, necessitating hardware, software, and cloud-based solutions investments. Additionally, ensuring data security and privacy is paramount, particularly in financial data, which is highly sensitive and subject to regulatory requirements (Ullah, Sepasgozar, Thaheem, & Al-Turjman, 2021).

Furthermore, maintaining and updating ML models over time is a continuous challenge. Machine learning models need to be regularly retrained with new data to ensure their predictions remain accurate and relevant. This requires ongoing monitoring, evaluation, and maintenance efforts, which can be resource-intensive. Developing automated pipelines for data ingestion, model training, and deployment can help streamline this process, but it requires significant technical expertise and investment (Prapas, Derakhshan, Mahdiraji, & Markl, 2021).

5. Conclusion

In this paper, we explored the transformative potential of machine learning (ML) in budget forecasting for corporate finance. We began by discussing the importance of accurate budget forecasting in financial planning and how traditional methods often fall short in handling complex and dynamic data. We then examined the theoretical foundations of machine learning, highlighting key techniques such as regression, time series analysis, and neural networks that are particularly relevant for financial forecasting. Following this, we introduced a conceptual model for integrating ML into budget forecasting, detailing its components, architecture, and expected benefits, including improved accuracy and efficiency. Lastly, we addressed the challenges and considerations, such as data quality, ethical concerns, and organizational barriers, that must be navigated to successfully implement ML-driven forecasting.

The proposed model has significant implications for corporate financial planning. By leveraging machine learning, companies can achieve more accurate and reliable budget forecasts, which are crucial for making informed strategic decisions. The enhanced accuracy of ML models allows for better risk management and resource allocation, helping companies optimize their financial performance. Additionally, the efficiency gained through automation reduces the time and effort required for manual data processing and analysis, freeing up finance professionals to focus on higher-value tasks such as strategic planning and decision-making.

Moreover, the adaptability of ML models ensures that forecasts remain relevant in rapidly changing business environments. Unlike static traditional models, ML algorithms can continuously learn from new data and adjust their predictions accordingly. This dynamic nature of ML-driven forecasting provides companies with a competitive edge, enabling them to respond swiftly to market changes and emerging trends. Furthermore, the deeper insights generated by ML models, which analyze multiple variables and their interactions, offer a more comprehensive view of financial performance. This holistic understanding helps companies to proactively address challenges and capitalize on opportunities, driving better financial outcomes.

5.1. Recommendations for Future Research and Practical Implementation

Further research and practical efforts are needed to fully harness the potential of machine learning in budget forecasting. One key area for future research is the development of more advanced ML algorithms that can handle the unique complexities of financial data. This includes improving the interpretability of models to ensure that finance professionals can understand and trust the predictions generated by ML systems. Additionally, research should focus on addressing ethical concerns, such as bias and fairness, to ensure that ML models do not perpetuate or exacerbate existing inequalities.

Practical implementation of ML-driven forecasting requires a strategic approach. Organizations should invest in building robust data infrastructures that support collecting, storing, and processing large datasets. This involves implementing data warehouses, cloud storage solutions, and data integration platforms. It is also crucial to foster a data-driven culture within the organization by encouraging collaboration between finance professionals and data scientists. Training programs and workshops can help finance teams develop the necessary skills to work effectively with ML models.

Furthermore, organizations should establish governance frameworks to manage data privacy, security, and ethical considerations. Regular audits and evaluations of ML models are necessary to ensure their performance and fairness over time. Finally, developing automated pipelines for data ingestion, model training, and deployment can streamline the ML implementation process and ensure that forecasts remain accurate and up-to-date.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest exists among the Authors.

References

[1] Abdulla, N., Demirci, M., & Ozdemir, S. (2022). Design and evaluation of adaptive deep learning models for weather forecasting. Engineering Applications of Artificial Intelligence, 116, 105440.

[2] Belenguer, L. (2022). AI bias: exploring discriminatory algorithmic decision-making models and the application of possible machine-centric solutions adapted from the pharmaceutical industry. AI and Ethics, 2(4), 771-787.

[3] Biju, A. K. V. N., Thomas, A. S., & Thasneem, J. (2024). Examining the research taxonomy of artificial intelligence, deep learning & machine learning in the financial sphere—a bibliometric analysis. Quality & Quantity, 58(1), 849-878.

[4] Birim, S., Kazancoglu, I., Mangla, S. K., Kahraman, A., & Kazancoglu, Y. (2024). The derived demand for advertising expenses and implications on sustainability: a comparative study using deep learning and traditional machine learning methods. Annals of Operations Research, 339(1), 131-161.

[5] Chan, J. Y.-L., Leow, S. M. H., Bea, K. T., Cheng, W. K., Phoong, S. W., Hong, Z.-W., & Chen, Y.-L. (2022). Mitigating the multicollinearity problem and its machine learning approach: a review. Mathematics, 10(8), 1283.

[6] de Zarzà, I., de Curtò, J., Roig, G., & Calafate, C. T. (2023). Optimized financial planning: integrating individual and cooperative budgeting models with LLM recommendations. AI, 5(1), 91-114.

[7] Hardt, M., & Recht, B. (2022). Patterns, predictions, and actions: Foundations of machine learning: Princeton University Press.

[8] Irfan, M., Elhoseny, M., Kassim, S., & Metawa, N. (2023). Advanced machine learning algorithms for complex financial applications: IGI Global.

[9] Kang, Y., Cai, Z., Tan, C.-W., Huang, Q., & Liu, H. (2020). Natural language processing (NLP) in management research: A literature review. Journal of Management Analytics, 7(2), 139-172.

[10] Kim, B., Park, J., & Suh, J. (2020). Transparency and accountability in AI decision support: Explaining and visualizing convolutional neural networks for text information. Decision Support Systems, 134, 113302.

[11] Lai, Y., & Dzombak, D. A. (2020). Use of the autoregressive integrated moving average (ARIMA) model to forecast near-term regional temperature and precipitation. Weather and forecasting, 35(3), 959-976.

[12] Latif, S., Rana, R., Khalifa, S., Jurdak, R., Qadir, J., & Schuller, B. W. (2020). Deep representation learning in speech processing: Challenges, recent advances, and future trends. arXiv preprint arXiv:2001.00378.

[13] Machireddy, J. R., Rachakatla, S. K., & Ravichandran, P. (2021). Leveraging AI and Machine Learning for Data-Driven Business Strategy: A Comprehensive Framework for Analytics Integration. African Journal of Artificial Intelligence and Sustainable Development, 1(2), 12-150.

[14] Mahalakshmi, V., Kulkarni, N., Kumar, K. P., Kumar, K. S., Sree, D. N., & Durga, S. (2022). The role of implementing Artificial Intelligence and Machine Learning technologies in the financial services Industry for creating competitive intelligence. Materials Today: Proceedings, 56, 2252-2255.

[15] Masini, R. P., Medeiros, M. C., & Mendes, E. F. (2023). Machine learning advances for time series forecasting. Journal of economic surveys, 37(1), 76-111.

[16] Miceli, A., Hagen, B., Riccardi, M. P., Sotti, F., & Settembre-Blundo, D. (2021). Thriving, not just surviving in changing times: How sustainability, agility and digitalization intertwine with organizational resilience. Sustainability, 13(4), 2052.

[17] Michailidis, P., Michailidis, I., Gkelios, S., & Kosmatopoulos, E. (2024). Artificial Neural Network Applications for Energy Management in Buildings: Current Trends and Future Directions. Energies, 17(3), 570.

[18] Nguyen, D. K., Sermpinis, G., & Stasinakis, C. (2023). Big data, artificial intelligence and machine learning: A transformative symbiosis in favour of financial technology. European Financial Management, 29(2), 517-548.

[19] Ogugua, J. O., Okongwu, C. C., Akomolafe, O. O., Anyanwu, E. C., & Daraojimba, O. D. (2024). Mental health and digital technology: a public health review of current trends and responses. International Medical Science Research Journal, 4(2), 108-125.

[20] Okoduwa, I. O., Ashiwaju, B. I., Ogugua, J. O., Arowoogun, J. O., Awonuga, K. F., & Anyanwu, E. C. (2024). Reviewing the progress of cancer research in the USA. World Journal of Biology Pharmacy and Health Sciences, 17(2), 068-079.

[21] Pichler, M., & Hartig, F. (2023). Machine learning and deep learning—A review for ecologists. Methods in Ecology and Evolution, 14(4), 994-1016.

[22] Prapas, I., Derakhshan, B., Mahdiraji, A. R., & Markl, V. (2021). Continuous training and deployment of deep learning models. Datenbank-Spektrum, 21(3), 203-212.

[23] Rane, N. L., Choudhary, S. P., & Rane, J. (2024). Artificial Intelligence-driven corporate finance: enhancing efficiency and decision-making through machine learning, natural language processing, and robotic process automation in corporate governance and sustainability. Studies in Economics and Business Relations, 5(2), 1-22.

[24] Rudin, C., Chen, C., Chen, Z., Huang, H., Semenova, L., & Zhong, C. (2022). Interpretable machine learning: Fundamental principles and 10 grand challenges. Statistic Surveys, 16, 1-85.

[25] Schaffer, A. L., Dobbins, T. A., & Pearson, S.-A. (2021). Interrupted time series analysis using autoregressive integrated moving average (ARIMA) models: a guide for evaluating large-scale health interventions. BMC medical research methodology, 21, 1-12.

[26] Schmidt, P. J., Riley, J., & Swanson Church, K. (2020). Investigating accountants' resistance to move beyond Excel and adopt new data analytics technology. Accounting Horizons, 34(4), 165-180.

[27] Sen, J., Sen, R., & Dutta, A. (2022). Introductory chapter: machine learning in finance-emerging trends and challenges. Algorithms, Models and Applications, 1.

[28] Taye, M. M. (2023). Understanding of machine learning with deep learning: architectures, workflow, applications and future directions. Computers, 12(5), 91.

[29] Udegbe, F. C., Ebulue, O. R., Ebulue, C. C., & Ekesiobi, C. S. (2024a). Machine Learning in Drug Discovery: A critical review of applications and challenges. Computer Science & IT Research Journal, 5(4), 892-902.

[30] Udegbe, F. C., Ebulue, O. R., Ebulue, C. C., & Ekesiobi, C. S. (2024b). Precision Medicine and Genomics: A comprehensive review of IT-enabled approaches. International Medical Science Research Journal, 4(4), 509-520.

[31] Udegbe, F. C., Ebulue, O. R., Ebulue, C. C., & Ekesiobi, C. S. (2024c). The role of artificial intelligence in healthcare: A systematic review of applications and challenges. International Medical Science Research Journal, 4(4), 500-508.

[32] Ullah, F., Sepasgozar, S. M., Thaheem, M. J., & Al-Turjman, F. (2021). Barriers to the digitalisation and innovation of Australian Smart Real Estate: A managerial perspective on the technology non-adoption. Environmental Technology & Innovation, 22, 101527.

[33] Venkataramanan, S., Sadhu, A. K. R., Gudala, L., & Reddy, A. K. (2024). Leveraging Artificial Intelligence for Enhanced Sales Forecasting Accuracy: A Review of AI-Driven Techniques and Practical Applications in Customer Relationship Management Systems. Australian Journal of Machine Learning Research & Applications, 4(1), 267-287.

[34] Wasserbacher, H., & Spindler, M. (2022). Machine learning for financial forecasting, planning and analysis: recent developments and pitfalls. Digital Finance, 4(1), 63-88.

[35] Yang, L., & Shami, A. (2022). IoT data analytics in dynamic environments: From an automated machine learning perspective. Engineering Applications of Artificial Intelligence, 116, 105366.

[36] Zhong, S., Zhang, K., Bagheri, M., Burken, J. G., Gu, A., Li, B., . . . Schrier, J. (2021). Machine learning: new ideas and tools in environmental science and engineering. Environmental science & technology, 55(19), 12741-12754.