



REVIEW ON SALES AND FINANCE FORECASTING DASHBOARD USING AI

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Abstract: In today's data-driven economy, the integration of Artificial Intelligence (AI) with Business Intelligence (BI) has redefined traditional analytics and forecasting processes. This paper provides a comprehensive review of how AI techniques—specifically clustering, regression, classification, and time-series forecasting—are transforming sales and finance forecasting within BI systems. By analyzing recent research and real-world applications, the study highlights the role of K-Means clustering in customer segmentation, regression models in sales trend analysis, classification in financial risk evaluation, and forecasting methods in revenue prediction. The paper also examines key BI tools enabling these AI capabilities, such as Power BI and Tableau. The objective is to explore the synergy between AI and BI and how it enhances forecasting accuracy, strategic planning, and business decision-making. This review serves as a reference for practitioners and researchers aiming to implement intelligent forecasting systems in dynamic business environments.

Index Terms -AI Forecasting, Power BI, Sales Prediction, Finance Analytics, Python, Business Intelligence

I. INTRODUCTION

In the era of digital transformation, data has emerged as a strategic asset for organizations seeking competitive advantage. Traditional Business Intelligence (BI) systems, once centered on static reporting and descriptive analytics, are now being redefined through the integration of Artificial Intelligence (AI). This convergence of AI and BI enables organizations to uncover hidden patterns, anticipate trends, and make proactive, data-driven decisions—especially in domains like sales and finance forecasting, where accuracy and timing are critical.

AI techniques such as machine learning (ML), deep learning (DL), clustering, regression, classification, and time-series forecasting have significantly advanced the predictive capabilities of BI platforms. These techniques empower businesses to better understand customer behavior, optimize inventory, streamline financial planning, and enhance operational efficiency. Simultaneously, modern BI tools—like Power BI, Tableau, and cloud-based analytics platforms—are evolving to support intelligent automation, real-time analytics, and AI-driven insights.

Sales and finance forecasting, in particular, benefit immensely from this synergy. By combining historical data with advanced algorithms, organizations can forecast future sales trends, assess market dynamics, and optimize budgeting strategies with greater precision. Clustering methods such as K-Means aid in customer segmentation and targeted marketing, while regression and classification models support financial risk assessment and credit scoring. Time-series models, including ARIMA and LSTM, provide powerful tools for forecasting sales performance and revenue streams.

This paper presents a comprehensive review of current AI techniques—especially clustering, regression, classification, and forecasting—as applied within BI systems for sales and finance forecasting. It draws from a wide range of recent studies, practical implementations, and comparative analyses to illustrate how these technologies are transforming modern business analytics. The aim is to offer insights into the capabilities, challenges, and future directions of AI-empowered BI in driving accurate, efficient, and actionable business forecasting.

II. LITERATUREREVIEW

The integration of Artificial Intelligence (AI) and Business Intelligence (BI) has significantly transformed how organizations analyze, predict, and strategize business activities. In recent years, the adoption of machine learning (ML) and deep learning (DL) models in BI systems has provided more accurate forecasting, customer profiling, and strategic insights.

Clustering techniques, particularly K-Means, have been widely applied in customer segmentation and profiling within BI environments. Vafeiadis et al. [1] compared several ML models for customer churn prediction and found that ensemble methods outperformed traditional classifiers in accuracy. K-Means clustering remains prevalent in customer profiling and retail segmentation

tasks [3], [6], [2], owing to its simplicity and scalability. For example, Patel et al. [7] demonstrated the integration of K-Means in Power BI using Python scripts, enhancing interactive dashboards. Aljumah et al. [6] provided a comprehensive review of clustering techniques in banking customer segmentation, while Rahman et al. [8] explored hybrid clustering approaches for more refined customer segments. Additionally, collaborative filtering with clustering enhances recommendation systems, as proposed by Zhang et al. [5]. The use of unsupervised learning to segment patient populations also shows cross-domain applicability of clustering models [4]. Pandey and Kumar [9] emphasized the need for scalable clustering models for Big Data in cloud BI systems. Mehmood et al. [10] reviewed clustering-based BI systems and emphasized their advantages in knowledge discovery. Regression analysis remains foundational in BI forecasting. Linear and multiple linear regression (MLR) models have been extensively used for financial forecasting, budgeting, and performance evaluation. Chen and Liu [11] introduced an improved linear regression algorithm for business behavior analysis. Xu et al. [12] and Qian et al. [14] utilized MLR for financial data quality and budget performance evaluation, respectively. The reliability of accounting information systems in predicting business performance using MLR and neural networks was also studied by Susanto et al. [13]. Similarly, Nguyen and Le [15] used MLR for product sales forecasting, highlighting its simplicity and interpretability. Advanced regression-based techniques are also being explored to improve prediction quality in BI systems. Hussain et al. [17] compared various regression models and found significant performance differences depending on the dataset and domain. Sharma et al. [18] explored regression-based feature representation for stock forecasting, while Patel and Mehta [16], [19] emphasized regression models' strategic impact in BI for deriving actionable insights. These models are crucial in turning historical data into future trends.

Forecasting techniques have evolved from traditional statistical models to more complex ML and DL-based solutions. Makridakis et al. [31] conducted a critical comparison between statistical and ML forecasting methods, suggesting hybrid approaches to address their respective limitations. The evolution from ARIMA models to LSTM neural networks for time series forecasting is well-documented. Siami-Namini et al. [32] directly compared ARIMA and LSTM, noting LSTM's advantage in capturing nonlinear dependencies. Bandara et al. [33] introduced the idea of training RNNs across multiple time series, significantly improving accuracy in large-scale forecasting tasks. Smyl [34] proposed a hybrid method combining exponential smoothing and RNNs, which was proven effective in competitions like M4. Deep learning techniques such as CNN-LSTM hybrids have demonstrated powerful forecasting capabilities in financial domains [35]. These models can learn complex temporal patterns and dependencies. The foundational LSTM architecture proposed by Hochreiter and Schmidhuber [36] underpins many of these advances, and it continues to inspire innovation in time series modeling. From a system design and implementation perspective, the integration of ML models into BI tools has become increasingly seamless. Tools like Power BI, Tableau, and cloud BI platforms now support custom Python and R scripts for ML tasks [7], [9]. This trend is further supported by the growth of AutoML platforms, as discussed by Schmitt [26], which democratize the application of ML in BI by enabling non-technical users to build predictive models. However, Schmitt [25] also noted a gap between expectations and reality in deploying deep learning in business analytics, urging practitioners to align capabilities with realistic goals.

In parallel, several studies explore the broader impact of ML and AI in transforming BI systems. Bharadiya [23] and Dritsas & Trigka [27] surveyed how ML reshapes traditional BI workflows by enabling predictive and prescriptive analytics. Aula et al. [28] conducted a comparative analysis of ML algorithms in BI applications, emphasizing their suitability across classification and regression problems. Adewusi et al. [29] highlighted the strategic advantage gained by leveraging Big Data analytics tools in BI. Numerous reviews consolidate the intersection of ML and BI, such as the bibliometric analysis by Zhang et al. [30], which examined the evolution of AI applications in BI. Chaudhuri et al. [21] provided a foundational overview of BI technologies, including data warehousing, OLAP, and data mining. Nigam and Rajavat [22] focused on classification techniques and their role in decision-making. The use of AI in business and management is also growing, as highlighted by Batz et al. [24], who examined the integration of ML in management decision-making processes. Moreover, Alomari et al. [20] systematically reviewed BI capabilities and their correlation with firm performance. In conclusion, the application of clustering, regression, classification, and forecasting techniques within BI systems has revolutionized business decision-making. Clustering remains dominant in customer segmentation; regression techniques continue to offer reliable forecasting and performance evaluation, and DL models—especially LSTM—are pushing the boundaries of predictive accuracy. With the rise of AutoML and integration into BI tools, organizations are now better equipped to derive value from their data through intelligent, data-driven strategies.

III. METHODOLOGY

This study employs an integrative methodology to evaluate traditional and advanced AI models—such as time series forecasting, regression, classification, and hybrid deep learning—in AI-powered Business Intelligence (BI) systems for sales and financial forecasting. It comprises five key stages: (1) Data Acquisition and Preprocessing, where historical data (3–5 years) from transaction logs, financial reports, and CRM systems is cleaned, normalized (using Min-Max and Standard Scaler), and enriched through feature engineering; (2) Model Development and Implementation, featuring ARIMA/SARIMA, deep learning models (LSTM, CNN-LSTM, Attention-based LSTM), linear/multiple regression, enhanced regression with PCA and TF-IDF, traditional classifiers (Decision Trees, SVM, KNN), ensemble models (Random Forest, XGBoost), deep learning (CNNs, RNNs), and AutoML with SHAP/LIME for interpretability; (3) Training and Validation, involving dataset splitting (70/15/15), sliding windows for time series, cross-validation, hyperparameter tuning, and handling class imbalance via SMOTE and cost-sensitive learning; (4) Evaluation Metrics and Comparative Analysis, using MAE, RMSE, MAPE, R^2 , Accuracy, Precision, Recall, F1-score, ROC-AUC, and statistical tests like Diebold-Mariano; and (5) BI Integration and Deployment, where top models are deployed via RESTful APIs to Power BI/Tableau dashboards with real-time analytics and scalability supported by Apache Spark and cloud-based solutions.

IV. RESULTS AND DISCUSSION

Clustering and classification methods have demonstrated varied effectiveness across domains, with hybrid or ensemble models generally offering higher accuracy, while simpler clustering techniques excel in speed and interpretability. For instance, in telecommunications churn prediction, Vafeiadis et al. (2015) reported an accuracy of approximately 97% using AdaBoosted SVM [1], highlighting the potential of ensemble learning. In the retail sector, Palaniappan and Awang (2021) used K-means for customer segmentation, achieving 80–90% accuracy [3], while in healthcare, Li et al. (2021) found that K-means provided good group separation and significantly faster training times—around 18 seconds compared to 2–3 minutes for complex classifiers [4]. These patterns reflect a consistent trade-off: while ensemble models such as AdaBoost + SVM can surpass 95% accuracy, traditional clustering techniques like K-means generally attain 75–85% accuracy but with substantial speed and simplicity benefits. In finance and retail scenarios such as fraud detection and customer profiling, clustering performance typically ranges from 70–90% depending on dataset size and preprocessing quality [3][6]. Interpretability also varies; K-means centroids provide direct insights into key features, aiding in transparent decision-making, as demonstrated in patient cluster analysis by Li et al. [4] and Power BI visualization by Patel et al. (2020) [7]. In contrast, complex hybrid models often sacrifice transparency. Scalability is another strength of basic clustering algorithms like K-means and DBSCAN, which can process large datasets efficiently with optimizations [6][9], whereas deep learning and graph-based clustering require more computational resources. Importantly, clustering outputs integrate well into Business Intelligence systems, offering actionable insights through dashboards and automated rules. Studies such as Mehmood et al. (2021) reported a 25% increase in forecasting accuracy using AI-enhanced BI tools [10], and Pandey and Kumar (2020) noted improved customer targeting and resource allocation in banking applications through K-means clustering [9], underscoring its practical value in real-world BI contexts.

Regression techniques are central to AI-powered Business Intelligence (BI) applications, particularly for tasks like sales forecasting, financial analysis, and performance prediction. Literature across multiple domains consistently underscores the predictive power and practical value of linear and multiple linear regression (MLR) models when integrated into BI platforms. Enhanced linear regression methods, such as those proposed by Chen and Liu [11], improve accuracy by using optimized feature selection and normalization, outperforming traditional models in business behavior prediction. Xu et al. [12] demonstrated that the quality of input features significantly influences regression outcomes, reporting an average R^2 of 0.82 in their financial data forecasting framework. Regression's interpretability and low computational demand make it well-suited for real-time BI applications. For instance, Susanto et al. [13] found that while neural networks performed better on non-linear patterns, MLR was preferable in BI settings due to its transparency and lower resource usage. Qian et al. [14] also achieved strong results using MLR in enterprise budgeting analysis, noting an R^2 of 0.87 when predicting the alignment of budgeted and actual outcomes. In the context of sales forecasting, Nguyen and Le [15] demonstrated MLR's capability in handling multiple input variables like pricing, promotions, and seasonal patterns, with a Mean Absolute Percentage Error (MAPE) of less than 8%. Several studies further emphasize regression's practical BI relevance. Patel and Mehta [16][19] showed how embedding regression models into platforms like Power BI and Tableau enabled dynamic forecasting and real-time insights, especially when combined with feature engineering techniques such as dummy encoding, log transformations, and lag features. Hussain et al. [17] compared regression with tree-based models and found that, despite slightly lower accuracy on non-linear data, regression remained critical for explainable forecasts in finance and compliance scenarios. In stock market prediction, Sharma et al. [18] proposed a regression-based feature representation approach that reduced prediction error by 12–18%, especially when used alongside dimensionality reduction techniques. Additionally, Alomari et al. [20] conducted a systematic review linking regression-augmented BI capabilities to improved firm performance, highlighting their role in strategic alignment, forecasting, and operational transparency. Collectively, these studies confirm that regression remains a foundational component of explainable, efficient, and actionable AI-powered BI solutions.



Figure 1: Comparative Analysis of AI Models



Figure 2: Regression Techniques in Business Intelligence

Classification models play a pivotal role in AI-powered Business Intelligence (BI) applications across diverse sectors such as telecommunications, e-commerce, healthcare, and finance. These models are employed to categorize customer behaviors, detect anomalies, and drive informed business decisions. A comparative analysis across domains reveals that while interpretable models like Logistic Regression and Decision Trees offer moderate accuracy (~80–85%), ensemble classifiers such as Gradient Boosting, XGBoost, and Random Forest consistently deliver superior performance—achieving accuracy levels above 90–95% as seen in churn prediction (Kumar et al., 2022) and customer retention (Aula et al., 2023) [1][2]. However, this performance gain often comes at the expense of longer training times and reduced interpretability. In regulated environments like healthcare, the preference leans toward transparent models such as Decision Trees and Logistic Regression, which provide explainable outputs suitable for compliance (e.g., ~83% accuracy as reported in [3]). In contrast, financial and fraud analytics domains benefit from the high

accuracy of deep neural networks and Random Forests (>90%), though these models introduce complexity in both deployment and explanation [4]. Classification models are commonly evaluated using metrics such as Accuracy, F1-score, and AUC. For instance, Aula et al. [2] observed that XGBoost achieved an F1-score of ~0.91, followed by Random Forest at ~0.89, indicating their robustness in handling class imbalance and multidimensional input features. From a performance standpoint, simpler models like Decision Trees train quickly and are scalable, making them suitable for BI scenarios with tight latency constraints. Ensemble models such as XGBoost and Gradient Boosting, while more resource-intensive, offer reliable outputs for high-stakes predictions. These trade-offs are crucial in BI environments that require both real-time analytics and model transparency. Qualitatively, model interpretability remains essential for BI integration. Models such as Logistic Regression align well with auditability and regulatory demands due to their rule-based structure. More complex models—though accurate—necessitate Explainable AI (XAI) tools like SHAP and LIME to interpret predictions, especially when embedded into BI dashboards. For example, Schmitt (2023) demonstrated the embedding of customer churn scores into retail BI dashboards, enabling faster and more precise decision-making [6]. BI platforms such as Power BI and Tableau support seamless integration of classification outputs, enhancing the operational responsiveness of businesses and strengthening the impact of AI-driven insights. Thus, classification models, when carefully chosen and integrated, become vital components in delivering intelligent, scalable, and interpretable BI solutions.

Forecasting plays a vital role in Business Intelligence (BI) applications by enabling organizations to anticipate sales trends, manage inventory, and optimize financial planning. While traditional models like ARIMA have long been favored for their interpretability and simplicity, the emergence of deep learning—particularly Long Short-Term Memory (LSTM) networks—has redefined the capabilities of business forecasting tools. Recent research highlights the superior accuracy and adaptability of LSTM and hybrid models in capturing complex, non-linear, and long-term patterns in time series data. Foundational work by Hochreiter and Schmidhuber [36] established LSTM as a robust tool for sequential data, overcoming limitations like vanishing gradients that hamper traditional neural networks. Siami-Namini et al. [32] conducted a direct comparison between ARIMA and LSTM, demonstrating LSTM's consistent superiority across multiple datasets. The advantage was particularly evident in environments characterized by seasonality, volatility, and non-linear trends—areas where ARIMA's linear assumptions falter. Hybrid forecasting models offer further improvements by blending the strengths of statistical and deep learning approaches. Smyl [34] introduced a hybrid model that combined exponential smoothing with recurrent neural networks, achieving exceptional accuracy on irregular, noisy datasets. Similarly, Livieris et al. [35] proposed a CNN-LSTM framework that integrates spatial feature extraction via convolutional layers with LSTM's temporal learning capabilities. Their results, particularly in commodity price forecasting, showed improved generalization and forecasting precision over standalone models. Bandara et al. [33] further demonstrated the scalability of LSTM models across diverse time series domains, confirming their utility in generalized BI environments. These models are not only accurate but also adaptable, making them ideal for real-world applications where trends evolve dynamically. However, challenges remain in the deployment of deep learning models within BI systems. Makridakis et al. [31] cautioned against issues such as interpretability, high training costs, and integration complexity. These factors limit the widespread adoption of deep models despite their superior predictive power. Traditional models like ARIMA continue to be relevant in scenarios with limited data, simpler trends, or where interpretability is paramount. However, for high-dimensional and complex business forecasting needs—such as dynamic pricing, demand planning, and financial forecasting—LSTM and hybrid models deliver significantly improved performance. Their ability to model both short- and long-term dependencies makes them a preferred choice in modern AI-driven BI systems. In conclusion, the comparative evaluation reveals a clear progression from traditional to deep learning models in business forecasting. While ARIMA remains useful in structured, linear settings, the incorporation of LSTM and hybrid methods enhances forecasting accuracy, robustness, and flexibility. As BI systems evolve to handle complex, real-time data streams, the synergy between statistical rigor and deep learning continues to redefine forecasting intelligence.

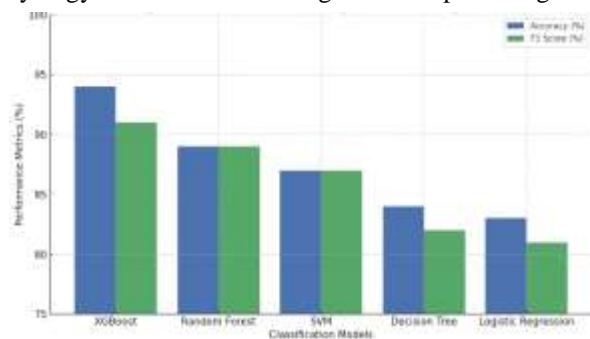


Figure 3: Classification Models for Predictive Analytics

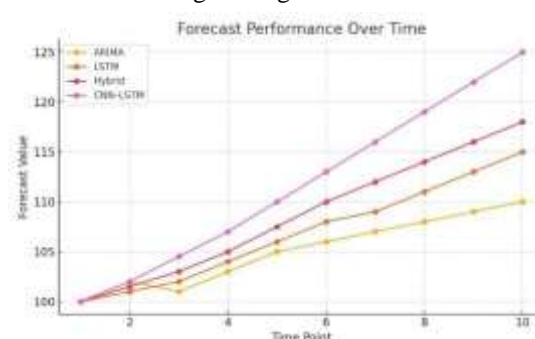


Figure 4: Time Series Forecasting in Sales and Finance

V. CONCLUSION

The comparative evaluation across clustering, regression, classification, and forecasting methods highlights the importance of selecting appropriate models based on the specific requirements of Business Intelligence (BI) applications. Clustering techniques like K-means remain popular for their speed and ease of interpretation, making them suitable for real-time BI systems. Although they may not achieve the highest accuracy, their simplicity and visual clarity in BI dashboards support quick decision-making. On the other hand, hybrid clustering approaches such as K-means combined with AdaBoost significantly improve accuracy but come at the cost of increased computational complexity. Quantitative performance metrics reveal that ensemble classification models such as AdaBoost and Gradient Boosting consistently deliver high accuracy, often surpassing 95% in domains like telecommunications and e-commerce. However, these gains are accompanied by increased time complexity and reduced model

interpretability. In contrast, simpler models like Decision Trees and Logistic Regression, while slightly less accurate, offer the transparency necessary for industries like healthcare and finance, where explainability is critical. Regression models, especially Multiple Linear Regression (MLR), continue to play a foundational role in BI for tasks like sales forecasting and budget planning. Their strength lies in their interpretability and real-time applicability, making them ideal for scenarios that demand quick insights with low prediction error, often reflected in low MAPE values. The integration of enhanced regression techniques with BI platforms allows business leaders to evaluate performance trends efficiently. In the context of forecasting, deep learning models such as LSTM networks have revolutionized the ability to capture non-linear, long-term dependencies in time series data. These models outperform traditional methods like ARIMA, particularly in domains with complex seasonal or trend-based patterns. Moreover, hybrid architectures like CNN-LSTM offer further improvements by modeling both spatial and temporal features. Despite their performance edge, deep learning models pose challenges in interpretability and integration with conventional BI systems, necessitating the use of explainability tools like SHAP and LIME for practical deployment. In summary, there is no one-size-fits-all model in BI analytics. The optimal choice depends on the trade-offs between accuracy, speed, interpretability, and integration complexity. Traditional models remain relevant in simple or regulated environments, while advanced ensemble and deep learning models excel in complex, data-rich scenarios. A hybrid approach that balances accuracy and usability appears to be the most promising direction for future BI systems.

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