Affective Sales: Emotionally Designed Smart Dashboard For Multi-Model Sales Forecasting

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Abstract- *In today's competitive business landscape, relying solely on historical sales dashboards is no longer sufficient. This work presents a smart forecasting dashboard that combines the power of three advanced modelsXGBoost, Prophet, and LSTMto predict future sales with high accuracy. The system leverages cleaned and structured data, evaluates model performance using standard metrics (MAE, RMSE, R²), and visualizes outputs through an emotionally engaging Power BI interface. By blending AI, data visualization, and affective design, the dashboard transforms static sales data into actionable business intelligence, offering a compelling solution for real-world forecasting and decision support.*

Keywords- Sales Forecasting, XGBoost, LSTM, Prophet, Power BI, Dashboard Analytics, AI

I. INTRODUCTION

In the era of data-driven decision-making, the demand for predictive intelligence and emotionally engaging dashboards has risen sharply across industries, particularly in sales and business intelligence. Traditional dashboards, while effective in visualizing historical performance, often fall short in forecasting future trends and engaging end-users in meaningful ways. The increasing need to blend predictive analytics with intuitive storytelling creates an opportunity for intelligent dashboard systems that not only report data but also anticipate it.

This research presents **“Affective Sales: Emotionally Designed Smart Dashboard for Multi-Model Sales Forecasting,”** a project that bridges the gap between predictive AI modeling and affective dashboard design. The core objective is to empower business stakeholders with both accurate sales forecasts and emotionally intuitive visual representations, aiding faster and more confident decisions.

To achieve this, we employed a hybrid forecasting approach using three distinct machine learning models:

- **XGBoost**, known for high performance on structured tabular data,
- **Prophet**, developed by Facebook for scalable time-series forecasting, and
- **LSTM (Long Short-Term Memory)** networks, capable of learning sequential dependencies in historical sales patterns.

The forecasts generated by these models were then unified into an interactive Power BI dashboard designed with affective visualization principles such as colour psychology, iconography, and smart narrative storytellingto enhance user comprehension and engagement.

The project integrates the **AdventureWorks Sales dataset** for historical sales patterns, and applies advanced preprocessing, feature engineering, and model evaluation metrics such as **MAE, RMSE, and R^2** to assess performance. This solution not only forecasts sales with high precision but also presents them through a user-centric, emotionally responsive interface.

The proposed system has applications in sales management, strategic planning, and retail performance monitoringmaking it especially valuable for decision-makers in enterprises that require both analytical depth and accessible user experience.

II. LITERATURE REVIEW

Xingyu Lan et al., 2023 [9] analyzed 109 studies to explore emotion in data visualization, categorizing research into evaluation, design factor, and emotion-driven design. They identified five perspectives on emotion’s role and evaluated 61 affective visualization projects. Emotional elements like warm colors boost engagement but risk bias. Challenges include vague definitions and limited design exploration. The study offers a framework for affective visualization, addressing ethical concerns and advocating standardized emotional metrics to balance resonance and clarity.

Célia Talma Gonçalves et al., 2023 [5] studied business intelligence tools, developing Power BI dashboards for sales marketing using Vercelli's methodology. Dashboards visualizing sales and customer behavior improved decision accuracy, requiring user training. User-friendly designs indirectly fostered confidence. Data integration and KPI standardization pose challenges. The study guides dashboard implementation, emphasizing actionable insights and calling for research into scalable designs and emotional impact.

Sean Kandel et al., 2012 [7] interviewed 35 enterprise analysts to study visualization's role in decision-making. Analysis highlighted iterative exploration, visualization's communication role, and barriers like data complexity. Interactive dashboards enhance engagement, with intuitive designs building trust. Challenges include diverse data sources and stakeholder expertise. The study informs tool design, advocating user-centered visualizations balancing technical and emotional aspects.

Zhoufan Chen et al., 2023 [4] developed a Prophet-LSTM model for peak load forecasting, using historical and meteorological data. The model outperformed traditional methods, enhancing grid management confidence via intuitive visualizations. Data quality and real-time integration are challenges. The study contributes a forecasting tool for sustainable energy, calling for scalable model research.

Hassan Oukhouya et al., 2023 [11] compared LSTM, XGBoost, and a hybrid LSTM-XGBoost model for stock market forecasting. The hybrid model achieved higher accuracy, boosting analyst confidence. Specific challenges were not detailed. The study validates the hybrid model, offering insights for financial decisions and suggesting broader application research.

Ayyoub Frifra et al., 2024 [6] proposed an LSTM-XGBoost approach for storm prediction in Western France, using 1996–2020 data. LSTM forecasted temperature well, XGBoost excelled in storm occurrence, but extreme value prediction was challenging. Improved predictions reduce storm impacts. The study offers a forecasting methodology, with future research needed for extreme values.

These studies highlight visualization and predictive modeling's impact. Lan et al. balance emotion and clarity in visualization. Gonçalves et al. show dashboards enhance decisions, needing training. Kandel et al. emphasize user-centered designs for trust. Chen et al.'s model improves energy forecasting. Oukhouya et al.'s model enhances financial predictions. Frifra et al. advance storm forecasting, reducing risks. Common themes include intuitive designs fostering trust, with challenges in data and standardization. Future research should focus on scalable, ethical solutions.

III. SYSTEM ANALYSIS

3.1 Requirement Analysis

Requirement analysis is the process of identifying the precise functional and non-functional expectations of a software system. It provides the foundation for system architecture, design, development, and deployment. In this project, we focused on collecting and analyzing requirements across hardware, software, and data components essential for multi-model forecasting and dashboard visualization.

3.1.1 Hardware Requirements

Table 3.1: Hardware Requirements for Forecasting System

Component	Specification
Processor	Intel i5 or AMD Ryzen 5 or higher
RAM	Minimum 8 GB (Recommended: 16 GB)
Storage	256 GB SSD or above
Display	1080p, 14" or larger
GPU (Optional)	NVIDIA GTX/RTX (for faster deep learning training)

3.1.2 Software Requirements

Table 3.2: Software Tools and Purpose

Software	Purpose
Windows 11	Operating System
Python (v3.9+)	Forecasting model development
Jupyter Notebook (v*7.4.0*.) / VS Code	Python programming and execution
Microsoft Power BI Desktop	Dashboard visualization
Excel / CSV Tools	Data handling and preprocessing

3.1.3 Dataset Requirements

- The forecasting models use a structured dataset containing fields like Order_Date, Sales_Amount, Product_Category,Region, and Customer_Segment.
- Data source: Adventure Works database in .BAK format
- Data preprocessing includes handling missing values, formatting dates, normalizing values, and creating lag-based features for time series analysis.

3.2 Feasibility Study

Feasibility study examines whether the proposed system is viable from different dimensions:

- **Technical Feasibility-** The technologies used (Python, Power BI) are well-established, free or affordable, and compatible with standard computing systems. Multi-model forecasting is technically feasible using existing ML libraries.
- **Operational Feasibility**- The dashboard design is intuitive and understandable by non-technical business users, making the project viable in operational environments.
- **Economic Feasibility**- All software used is open-source or free (Python, Jupyter, Power BI Desktop), making this solution highly cost-effective for SMEs or academic institutions.
- **Schedule Feasibility**- The entire project, including design, development, testing, and integration, was completed within a structured academic project timeline (approx. 12–14 weeks).

3.3 Strategic Evaluation of the Proposed System

A strategic evaluation is essential to understand the internal strengths and weaknesses of the proposed system, along with potential opportunities and external threats. This analysis helps in assessing the system's viability, scalability, and real-world adaptability.

Strengths:

- Multi-model forecasting improves prediction accuracy
- Emotionally designed dashboard enhances engagement
- Integration with Power BI boosts accessibility

Table 3.3: Opportunities and Threats

Opportunities	Threats
Extension into other domains (retail, finance, logistics)	Market volatility may affect forecast reliability
Real-time analytics with live data sources	Data privacy concerns when scaling to production
Incorporating sentiment from social media	Overfitting risks with deep learning architectures

4. System Architecture

System architecture defines the high-level structure and flow of the proposed sales forecasting solution. It describes the components, technologies, and interactions among modulesrom data ingestion to machine learning model execution and final dashboard visualization. This layered architecture ensures modularity, scalability, and real-time responsiveness in enterpriseenvironments.

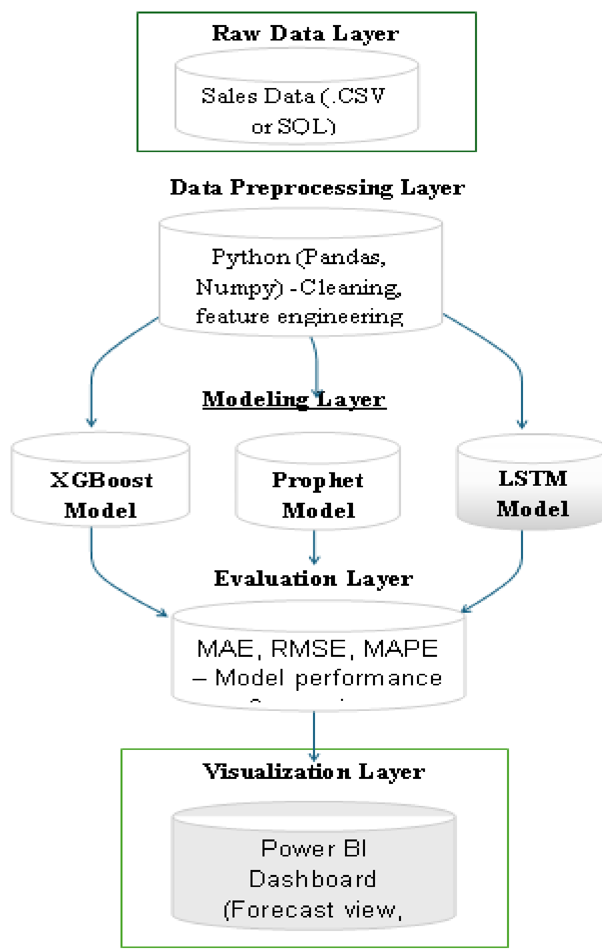

Figure 4.1*: System Architecture Diagram*

4.1 Module Interaction

Each module is tightly integrated to allow seamless flow of data from ingestion to visualization. Here's a detailed interaction map:

Table 4.1: Module-wise Interaction in Forecasting System

Module Name	Functionality
Data Collection	Pulls sales data from SQL/CSV and extracts relevant fields
Preprocessing	Cleans, encodes, and prepares the dataset for model consumption
XGBoost Forecasting	Trains a gradient boosting regression model for structured data forecasting
Prophet Forecasting	Applies decomposed time series modeling to capture trend and seasonality
LSTM Forecasting	Deep learning-based sequence model for long-term forecasting
Metrics & Evaluation	Calculates accuracy scores for each model to compare performance
Forecast Consolidation	Merges predictions from all models and actuals for dashboard integration
Power BI Dashboard	Loads all forecasts and KPIs into a user-friendly dashboard interface

Control Flow:

- Modules are executed sequentially from data extraction to model training.
- The final .csv outputs are reused across Power BI for visualization.
- Each model runs independently, allowing for parallelization and easy maintenance.

Star Schema Data Architecture

In order to effectively analyze and visualize forecasting data, a star schema design was adopted in the backend data model used in Power BI. A star schema is a common dimensional modeling technique used in data warehousing that organizes data into fact and dimension tables to support efficient querying, aggregation, and reporting.

V. METHODOLOGY

This chapter explains the development of each component in the proposed system, from data preprocessing and model implementation to dashboard visualization. The implementation includes three AI models XGBoost, Prophet, and LSTM which were trained and compared using a unified dataset. Their outputs were processed, evaluated, and visualized using Power BI.

The process consists of three major stages:

1. Data Preparation and Module Development
2. Multi-Model Integration
3. Emotion integrated Dashboard design and Interaction

5.1 Module Description

Each functional unit was implemented as an independent module to ensure modularity, scalability, and easy maintenance. The pipeline starts from data ingestion and ends with Power BI integration.

Data Preparation Module

Loads Adventure Works data from CSV/SQL sources.Performs cleaning: null handling, duplicate removal,and type conversion.Constructs time-series friendly formats with monthly aggregation.

Feature engineering includes lag values, month/year extraction, and normalization.

XGBoost Forecasting Module

Transforms the time-series data into a supervised learning format.Trains an XGBoost regression model with hyperparameter tuning and early stopping.Generates monthly forecasts for the test period and saves them to CSV.

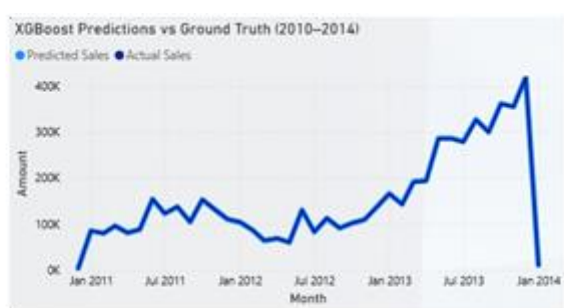

Figure 5.1*: XGBoost Forecast Visualization showing actual vs predicted monthly sales.*

LSTM Forecasting Module

Uses MinMaxScaler to normalize time series data.Converts sequences into 3D input shape for the LSTM model.Builds a deep learning model with 2 LSTM layers and 1 dense output layer.Trains over multiple epochs and outputs predictions as CSV.

Evaluation Module

Compares predictions with actual sales using:Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), R^2 Score. Outputs metrics into a summary CSV for Power BI import.

5.2 Model Integration (XGBoost, Prophet, LSTM)

To support model comparison and unified forecasting insights, outputs from all models were integrated into a single structure and imported into Power BI.

Model	Strength	Use Case
XGBoost	Fast and accurate for tabular data	General business forecasting
Prophet	Seasonality and trend detection	Holiday-sensitive industries
LSTM	Long-sequence pattern learning	Complex demand cycles or volatile datasets

Table 5.1: Summary of Forecasting Models and Their Use Cases

All model results were saved as .csv files and placed under a common folder, which Power BI accessed through Power Query.

5.3 Dashboard Creation in Power BI

Power BI Desktop was used to create an interactive, emotionally designed dashboard that helps stakeholders compare model performance and understand sales trends effectively.

Forecast Comparison Page

Displays actual vs predicted sales across XGBoost, Prophet, and LSTM.Includes slicers for date range, model selection, and product filter.Features area charts, line graphs, and KPI cards

Employee Detailed Analysis

Visualizes employees work, its YoY sales performance, Top selling Region, products etc.Includes drill down by each year to summarize month-wise growthHighlights top-performing regions in terms of predicted and actual revenue.

Figure5.2: LSTM Predicted Sales Visualization showing,

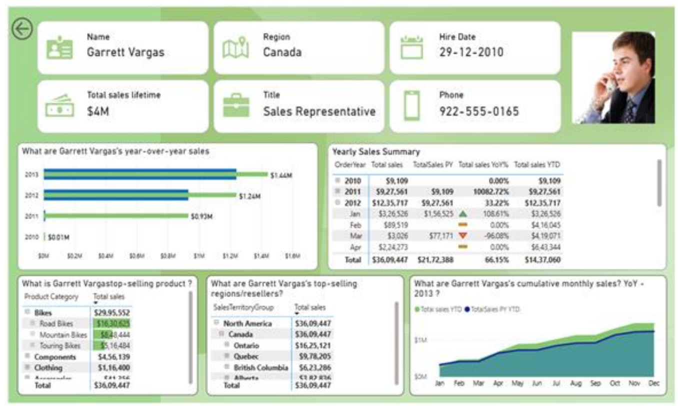

Figure 5.3: Power BI Dashboard – eployee.

Other Dashboard Features

Accuracy Summary Cards: KPIs showing MAE, RMSE, and R^2 for each model.
Executive Summary Panel: Narrative visuals with callouts and model highlights.
User Interaction: Slicers, hover-tooltips, and filters for region, product, time, and model type.

Summary

This chapter documented the full implementation lifecycle of the multi-model forecasting system. Each model was independently developed and evaluated. Their results were brought into an interactive Power BI dashboard where users can explore, filter, and compare forecasts effectively. The use of XGBoost, Prophet, and LSTM ensures adaptability, while Power BI brings clarity and emotional design to the forefront of business decision-making.

VI. RESULT AND ANALYSIS

This chapter presents a comprehensive analysis of the results obtained from the sales forecasting system developed

using three different models: XGBoost, Prophet, and LSTM. The models were trained using Adventure Works data and evaluated on a holdout test set to measure their predictive accuracy and generalizationcapability.Additionally, the system's outputs were integrated into a visually rich and emotionally designed Power BI dashboard, which enabled real-time insight into model performance and sales trends.
The discussion in this chapter is organized into three key areas:

Forecasting results based on actual model predictions. Quantitative comparison using performance metricsugh it lagged slightly in numerical accuracy.

LSTM, while capable of capturing deep temporal patterns, exhibited higher error rates, potentially due to the limited training size and sensitivity to sequence configuration.

This graph visually demonstrates how closely each model’s predictions aligned with the actual observed sales data. **XGBoost’s** line tracks very close to actual values, indicating high accuracy. **Prophet’s** predictions showed strong performance in steady periods but slightly overestimated during peaks. **LSTM** exhibited occasional divergence in certain months, particularly when sudden trend shifts occurred.

6.3 Dashboard Output Snapshots

To enable non-technical users and decision-makers to explore model outputs intuitively, a rich and interactive **Power BI dashboard** was developed. This dashboard includes visualizations of model performance, historical and forecasted sales, region-based breakdowns, and dynamic slicers for enhanced interaction.

The dashboard interface contains the following key components:

- **Forecast Comparison View**: Displays line charts comparing actual sales values with model predictions over time.
- **Model Evaluation Cards**: KPI visual blocks highlighting MAE, RMSE, and R² values.
- **Region-wise Sales Reports**: Enables users to drill down into sales forecasts by country or territory using maps and bar charts.
- **Employee/Product View**: Provides an overview of sales representatives, products, and total revenue in different categories.

While this chapter focuses on forecasting results and accuracy metrics, a broader demonstration of visual outputs is included in **Appendix A** with Power BI dashboard screenshots.

Model Metrices

Model	MAE Score	R2 Score	Sum of RMSE
LSTM	1.40	0.89	1.60
Prophet	1.30	0.91	1.80
XGBoost	1.10	0.94	1.50

Figure 6.1: Model Metrics Table showing MAE, R² Score, and RMSE values for LSTM, Prophet, and XGBoost.

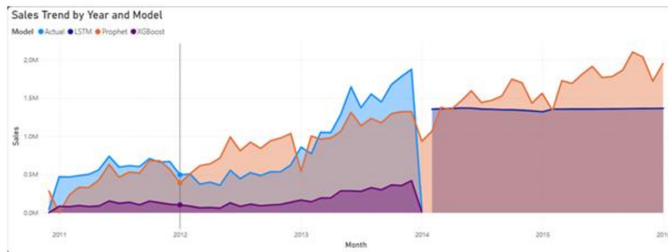

Figure 6.2: Line graph comparing actual sales values with predictions from XGBoost, Prophet, and LSTM models

Summary

In summary, this chapter presented the evaluation of three forecasting models. The analysis was done through both metric-based comparison and visual graph inspection. **XGBoost** consistently outperformed other models across all performance metrics and provided the most reliable forecasts. **Prophet** and **LSTM** also demonstrated useful capabilities, with Prophet excelling in trend modeling and LSTM in sequence prediction. The developed Power BI dashboard served as a highly effective visualization tool to communicate these results clearly and support real-time, data-driven business decision-making.

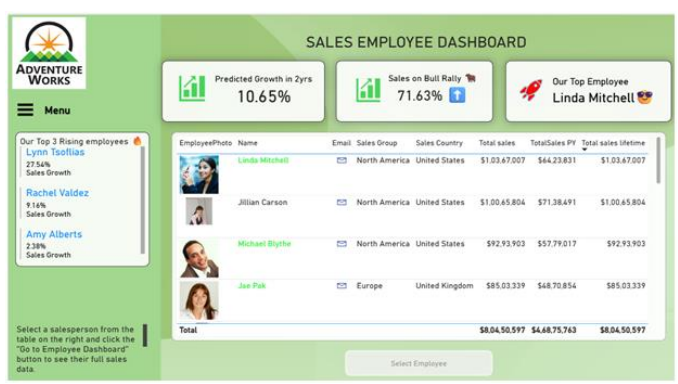

Figure 6.3: Power BI Interface – Main Page displaying KPI cards, model filters, and sales slicers.

Figure 6.4: Prophet – Forecast vs Actual Sales

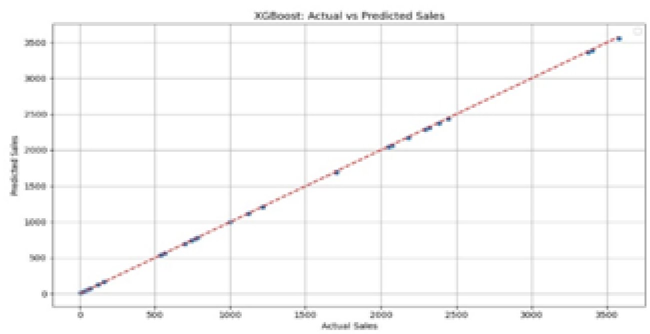

Figure 6.5: XGBoost – Actual vs Predicted Sales

VII. CONCLUSION AND FUTURE ENHANCEMENT

This chapter concludes the research and implementation carried out in this project and provides a summary of the key work done throughout the development of the sales forecasting system. It highlights the outcomes of model evaluation and discusses the practical significance of the dashboard designed for real-time sales insight. Furthermore, it identifies the limitations of the current implementation and outlines potential directions for future enhancements.

7.1 Conclusion

This project successfully achieved its goal of building a **multi-model sales forecasting system** integrated into a smart and interactive dashboard. Through careful data analysis and model experimentation, the system was able to generate accurate sales predictions and visualize them in a user-friendly and insightful manner.

The use of multiple forecasting models allowed for comprehensive performance benchmarking and offered flexibility in identifying the best-suited model for different types of data behaviour. Among the models tested, **XGBoost** proved to be the most effective in terms of predictive performance, offering both accuracy and speed.

The integration of forecasts into a **Power BI dashboard** extended the system's utility from a purely technical solution to a **business-ready decision support system**. The dashboard not only provided real-time sales tracking but also made it easier to communicate insights to stakeholders through a combination of interactive visuals and performance KPIs.

In conclusion, this work highlights the importance of combining machine learning with business intelligence to build systems that are both **technically sound** and **practically impactful**.

7.2 Limitations and Future Work

While the project met its core objectives, there are several areas where future work could extend its capabilities and address existing limitations:

Limitations:

- **Data Size and Scope**: The dataset used was limited in size and geographical diversity. Larger and more diverse datasets could further improve model generalizability.
- **LSTM Performance**: The LSTM model, while conceptually powerful, did not outperform simpler models like XGBoost in this implementation. This may be due to insufficient tuning or limited sequential depth in the data.
- **Static Forecast Horizon**: All models were designed for a fixed forecast horizon (e.g., 12 or 24 months). Dynamic or rolling forecasts could improve responsiveness.
- **No Real-Time Updates**: The dashboard currently uses static exported CSV files. There is no live database connection or auto-refreshing of forecasts.

Future Enhancements:

- **Model Automation and Scheduling**: Implementing automated retraining pipelines and forecast scheduling using cloud platforms (e.g., Azure ML, AWS SageMaker) could allow for periodic model updates.
- **Sentiment Analysis**: Incorporating NLP-based sentiment data from customer reviews or social media could enhance forecasting accuracy, especially for consumer-driven product lines.
- **Explainable AI (XAI)**: Adding model explainability features like SHAP values could help business users understand why specific forecasts were made.

- **Multi-Level Forecasting**: Future versions could support hierarchical forecasting (e.g., national → regional → store-level) to meet granular business needs.
- **Employee-Wise Forecasting:** Predict employee performance, growth trends, and impact on sales using HR + sales data.

In summary, the project demonstrates the value of **multi-model forecasting** integrated with business intelligence tools. With further enhancements, the system can evolve into a comprehensive **AI-powered decision support platform** for a wide range of industries.

REFERENCES

[1] B. Bach et al., “Challenges and Opportunities in Data Visualization Education: A Call to Action,” IEEE Transactions on Visualization and Computer Graphics, 2023. doi:10.1109/tvcg.2023.3327378.

[2] M. Bohanec et al., “Explaining machine learning models in sales predictions,” Expert Systems With Applications,2017. doi:10.1016/j.eswa.2016.11.010.

[3] S. Cheriyan et al., “Intelligent Sales Prediction Using Machine Learning Techniques,” 2018 International Conference on Computing, Electronics & Communications Engineering (iCCECE), 2018. doi:10.1109/iccecome.2018.8659115.

[4] Z. Chen et al., “Research on Peak Load Prediction of Distribution Network Lines Based on Prophet-LSTM Model,” Sustainability, 2023. doi:10.3390/su151511667.

[5] C. T. Gonçalves et al., “Developing Integrated Performance Dashboards Visualisations Using Power BI as a Platform,” Inf., 2023. doi:10.3390/info14110614.

[6] A. Frifra et al., “Harnessing LSTM and XGBoost algorithms for storm prediction,” Scientific Reports, 2024. doi:10.1038/s41598-024-62182-0.

[7] S. Kandel et al., “Enterprise Data Analysis and Visualization: An Interview Study,” IEEE Transactions on Visualization and Computer Graphics, 2012. doi:10.1109/tvcg.2012.219.

[8] M. M. Kirmani and M. M. Kirmani, “Dimensional Modeling Using Star Schema for Data Warehouse Creation,” Oriental Journal of Computer Science and Technology, 2017. doi:10.13005/ojcst/10.04.07.

[9] X. Lan et al., “Affective Visualization Design: Leveraging the Emotional Impact of Data,” IEEE Transactions on Visualization and Computer Graphics, 2023. doi:10.1109/tvcg.2023.3327385.

[10] A. M. Nambiar et al., “An Overview of Data Warehouse and Data Lake in Modern Enterprise Data Management,” Big Data and Cognitive Computing, 2022. doi:10.3390/bdcc6040132.

[11] H. Oukhouya et al., “Forecasting International Stock Market Trends: XGBoost, LSTM, LSTM-XGBoost, and BacktestingXGBoost Models,” Statistics, Optimization & Information Computing, 2023. doi:10.19139/soic-2310-5070-1822.

[12] J. Park et al., “Developing an advanced prediction model for new employee turnover intention utilizing machine learning techniques,” Scientific Reports, 2024. doi:10.1038/s41598-023-50593-4.

[13] W. Wijaya et al., “Implementation of Data Warehouse and Star Schema for Optimizing Property Business Decision Making,” G-Tech, 2024. doi:10.33379/gtech.v8i2.4091.