iJRASET
International Journal For Research in
Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 14 **Issue:** V **Month of publication:** May 2026

DOI: https://doi.org/10.22214/ijraset.2026.83284

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 14 Issue V May 2026- Available at www.ijraset.com

AI-Enhanced Business Intelligence Dashboard for Decision-Centric Predictive Analytics

C. Kalpana[1], Manoj Devare[2], Bhagya P Bijay Kumar[3]
Amity Institute of Information Technology, Amity University Mumbai, Mumbai.India

Abstract: Traditional business intelligence tools are used for the visualization of the data by the organizations, but the major problem is analysts have to make efforts to find the insights from this and also find the predictions on the basis of any one factor or metric; this makes the whole process time-consuming and difficult. This project proposes a framework focusing on decision-based analytics using a transactional dataset and creating a platform using Python and Streamlit that will provide a platform with options for data visualization and provide automated insights and predictions based on multiple variables with the help of a real-world dataset. The prediction model created using the Random Forest algorithm achieved an R^2 score of 0.99 and the Mean Absolute Error (MAE) of 37.93, thus the prediction deviation is low. This study also highlights the importance of Artificial Intelligence by implementing it the system using Machine Learning, showing how AI can help in advancing the dashboards from the traditional dashboards. The dashboard created will help to demonstrate how this proposed idea will enhance the efficiency and reduce the effort required for manually analyzing and interpreting and be easily usable by anyone, whether from a technical or non-technical field. The proposed system dashboard is reliable, time saving and requires less efforts, less complex and efficient.

Keywords: Business Intelligence, Data and Predictive Analysis, Machine Learning, Automated Insights, Streamlit, What-if Analysis

I. INTRODUCTION

In the current economy, which is data-driven, there is a generation of a huge amount of transactional data. This data can be used for interpreting the organization's work and making decisions for the future. Most of the companies use traditional business intelligence tools to visualize their historical data. But then these visualizations alone cannot be equal to getting insights.

The analysts have to spend lots of hours identifying the required details, like trends and changing variables, to see the change in patterns and so on. And all these tasks have to be done by them manually, which is time-consuming, brings a lag for interpretation, and makes the decision-making process slow and expensive.

Fig. 1. Traditional BI vs AI-Enhanced BI.

The challenge is twofold. First, traditional tools usually focus on univariate analysis. This means it looks at one metric at a time, but business outcomes are dependent on multiple variables. For example, an increase in revenue is rarely just because of a price drop; it happens because of the result of a combination of changes in variables like unit price, volume, and promotional timing. There is a technical barrier that stops the business decision-makers from using predictive models that are advanced. In real life they don't need to know the programming or code just for understanding the changes; for example, increasing the discount will increase or decrease the profit. Fig 1. shows the difference between the traditional BI and AI-enhanced BI. This project solves these inefficiencies by introducing a decision-centric framework built on a Python-Streamlit stack. By moving away from static dashboards, this research introduces an interactive environment where predictive modelling is baked into the UI. Using a Random Forest Regressor, the system analyzes the complex relationships within a real-world Amazon transactional dataset to provide instant "What-If" scenarios.

The main objective is to ensure that data science can be used by all. By integrating automated insights and Explainable AI (XAI) features—such as feature importance plots—the dashboard allows even people from non-technical backgrounds to also see and understand which factors are actually driving their revenue. Instead of "What happened?", changing to "What will happen if we change X?" It makes working with the data simpler, so organizations can act on insights more quickly.

II. RELATED WORK

In previous studies, instead of practical implementations, the concept of implementing AI and BI together is suggested in the form of a study in various papers, just suggesting some conceptual frameworks.

The usage of AI is mentioned to extend the business intelligence beyond the normal dashboards that are made by mentioning the need to enable automated insights for decision support [1]. Transformations that can be brought by AI-enhanced dashboards and their impact on business planning, and later their impact on company performance over various sectors, are compared [2]. Analytics based on AI can help in real-time insight generation, and AI will be the key element in future BI systems [3]. Automating the tasks of analysis of big data with the help of AU can increase the insight generation, and this will help the organizations to respond to the changes as fast as possible [4]. The existing business intelligence tools were reviewed, and the dashboard techniques suggest the importance of it in supporting managerial-level decision-making [5]. The combination of artificial intelligence and machine learning can help in improving predictive analytics by accurately forecasting and deciding the business strategy for the future [6].

These studies all suggest the potential of AI for transforming traditional BI and the need for developing tools for solving such gaps to save time and effort, helping the organizations.

Table 1 show cases the comparative analysis of related work.

TABLE I. COMPARITIVE ANALYSIS OF RELATED WORK

Ref	Title	Proposed Idea	Limitations
[1]	Ismael & Mohd (2025) – Beyond Dashboard: How AI Shaping Business Intelligence	Conceptual ideas about BI dashboards that are AI-enhanced can help in predictive decision support.	There is no practical or deployable implementation.
[2]	Jain (2023) – AI-Powered Business Intelligence Dashboards	Proposed AI dashboards for decision-making across sectors	Focused on theory, no practical implementation.
[3]	Shaffi (2024) – AI-Driven Analytics: The Future of Business Intelligence	Suggested idea for real-time automated insights.	They did not research about ease of use or efforts for analysts.
[4]	Cate (2025) – AI-Driven Automation of Big Data Insights for BI	Suggested idea of automating the analysis of big data with the help of AI.	They did not consider the usability for users from non-technical field.
[5]	Ezeilo et al. – Systematic Review of BI Tools and Dashboarding Techniques	they reviewed All the existing BI tools and dashboard methods.	Only skilled analysts can use the system easily.
[6]	Ramya et al. (2024) – AI and ML in Predictive Analytics	Suggested models of AI/ML for predicting the business outcomes.	They focused on models, not on a complete BI system.
This Work	From Visualization to Insight: A Decision-Centric Analytics Approach	A complete AI-based BI system built using Streamlit with transactional dataset, providing visualization, automated insights and multi-variable predictions.	There is a gap of real-time data integration.

III. NOVELTY

This framework is different from other works, as it not only shows the data but also predicts the outcomes using an interactive dashboard. The main contributions are:

A. Interactive Prediction and Multi-Variable Analysis

Unlike the usual systems, which show only fixed and pre-calculated values, in this proposed system, a random forest model is used to make predictions in real time. The user can provide inputs through the sliders provided in the interface and can also select sections from the interface made using Streamlit, allowing instant predictions. It provides various factors in the slider to adjust, thus helping to know the effect of combined factors. For example, users can easily see how the change in discount and unit price at the same time can affect the target variable.

B. Explainable Insights using Feature Importance

For the analysts and planners, it's important to know which factor contributes the most, so to solve this problem, Explainable AI is used to plot a graph showing the feature importance. This will help the system to show, percentage-wise, which input factor is more important and played the most important role in making the predictions. The system becomes easier to understand, trust and interpret.

C. Automated Insight Generation

The system has a section for automated insight generation that analyzes the transactional data (which is used for this study) using simple logic rules. Instead of calculating and getting the final insights manually, the system automatically does basic calculations like max and avg to get the summaries, which are easy to read and can be downloaded for later reference. This helps convert the raw numbers to direct statements so that they can be easily understood by decision makers.

D. Lightweight and Easy-to-Deploy BI System

From the system point of view, the analytics tool, which is simple and made using Python, Streamlit, and machine learning, is used for creating predictive model. This is an efficient tool and can be used with minor changes with various datasets. It's less complex and more advanced than the traditional BI tools.

IV. METHODOLOGY

The proposed system follows a structured workflow that transforms transactional data into meaningful insights through preprocessing, visualization, prediction, and automated interpretation. The dataset used for this study was first cleaned by removing records with missing values in key fields such as quantity, unit price, and discount. Only relevant attributes influencing revenue were retained for analysis. Basic standardization was applied to ensure consistency across visualizations and model inputs. The Streamlit-based dashboard allows users to interact with the system by selecting visualization, multi-variable prediction, or automated insights. For predictive analysis, a Random Forest regression model dynamically generates revenue estimates based on user-selected input values. Random Forest regression was selected due to its ability to model non-linear relationships and handle multi-variable data effectively [10]. Model performance was evaluated using R^2 and Mean Absolute Error (MAE) to ensure reliable predictions. Explainable AI techniques help improve transparency and trust in predictive models by highlighting feature contributions [11]. Fig 2. shows the workflow of the proposed analytic system approach. In detail each part is implemented as follows:

A. Data Collection and Preprocessing

The dataset used for showing the functionality of this proposed system is Amazon.csv. This is a transactional dataset with a large amount of data. Initially, before using any dataset, it should be prepared so that it doesn't contain any values that are missing and has standardized column names.

B. Visualization Layer

In the visualization section, the visualizations for the data are generated using the various graphs and charts with the help of matplotlib libraries. It would be similar to the other BI tools' visualization. We can visualize various things, like the sales performance of each brand, the revenue generated from each product, and many other such visualization graphs. These visual patterns will help make comparisons much easier that will also contribute to the decision-making process. Visual patterns are more suitable for comparisons, making it much clearer.

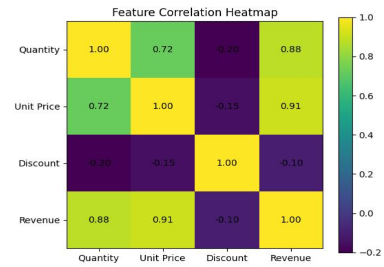


Fig. 2. Feature Correlation Heatmap

The correlation heatmap helps identify the relationship between different variables in the dataset. It shows that quantity and unit price have a strong positive correlation with revenue, while discount has comparatively lower influence.

C. Multi-Variable Predictive Analysis

In this paper, Random Forest algorithm is used for multi-variable prediction. Unlike the single input analysis, this is more useful as in reality the changes can happen because of multiple factors.

Let the Equation (1) for the feature vector be:

$$X = (x1, x2, x3, \ldots, x_n) \tag{1}$$

Where, the x1,x2,…, x_n are the input features.

So the Equation (2) according to this system for revenue predictions is:

$$TotalAmount = f(Quantity, UnitPrice, Discount) \tag{2}$$

Where,

- *f* represents the Random Forest regression model and
- The prediction will be generated dynamically based on user selected values.

This will help the users to analyze how the changes in various factors together will affect the predicted revenue.

D. Model Evaluation

For evaluating the model Equation(3) and Equation(4) is used. These equations are:

1) Mean Absolute Error (MAE):

MAE is used for measuring the average prediction error,

$$MAE = \frac{1}{n} \sum |Yactual - Ypredicted| \tag{3}$$

If the MAE value will be lower, then the prediction accuracy will be better.

2) Model performance using R^2 score:

This score helps to know how well the model can explain the variations in the data.

$$R^2 = 1 - \frac{Prediction\ Error}{Total\ Variance} \tag{4}$$

If the score is closer to 1, then it has a stronger model performance.

To evaluate the consistency and reliability of the predictive model, k-fold cross-validation technique was applied. The dataset was divided into several parts, allowing the model to be trained and tested multiple times on different data combinations. This process helps in checking how effectively the model performs on unseen data and ensures that the predictions are stable, accurate, and less prone to overfitting.

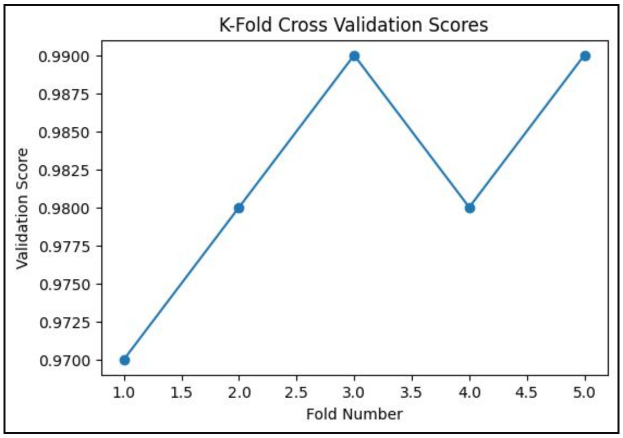


Fig. 3. K-Fold Cross-Validation Performance

E. Feature Importance

This shows the importance of each input variable to the final prediction. The values that are extracted using the Equation(5) is used for plotting the graph to show how each feature contributes to the prediction

$$Feature\ Importance\% = \frac{Contribution\ of\ Fetaure}{Total\ Contribution} * 100 \quad (5)$$

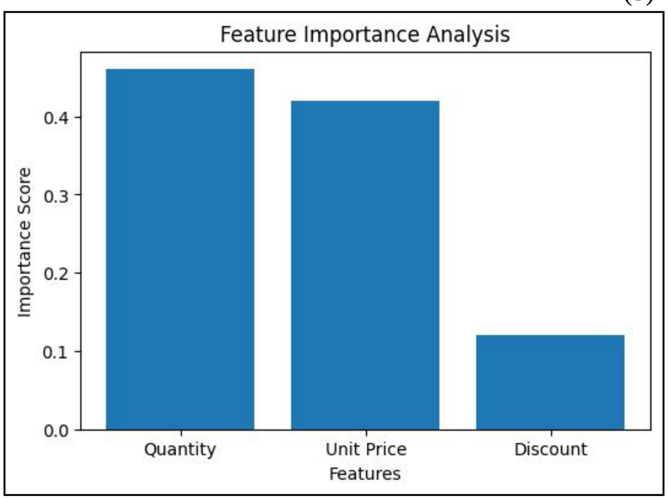


Fig. 4. Feature Importance Analysis

F. Generation of Automated Insights

Along with the other two options for visualization and prediction, the third option is to get automated insights and save them for later for planning and decision-making. This is implemented by structuring the data and finding the key drivers that will lead to making changes in the performance. Then grouping and summarizing these to highlight some important patterns. For example, summing the revenue by any category to find which category is the lead for generating

the revenue, etc. Then from the computed metrics, it's transformed to statements that can be understood by anyone, thus human-readable. So these will be derived directly from the data, no user intervention is required for manually writing it.

G. Implementation Environment

Python and Streamlit are used for implementing the idea to develop the interactive web-based dashboard with the options on the left side for viewing the data visualization, multi-variable analysis, and automated insights and providing these sections to switch between each other, making it an interactive dashboard.

ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 14 Issue V May 2026- Available at www.ijraset.com

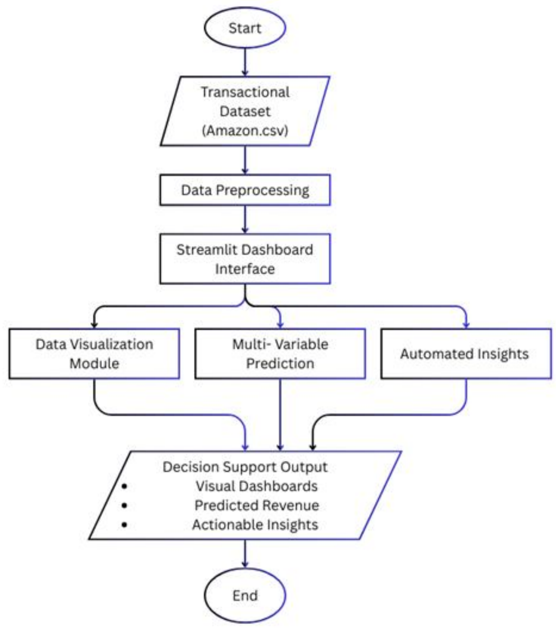


Fig.5. Proposed dashboard system workflow.

V. RESULTS AND DISCUSSION

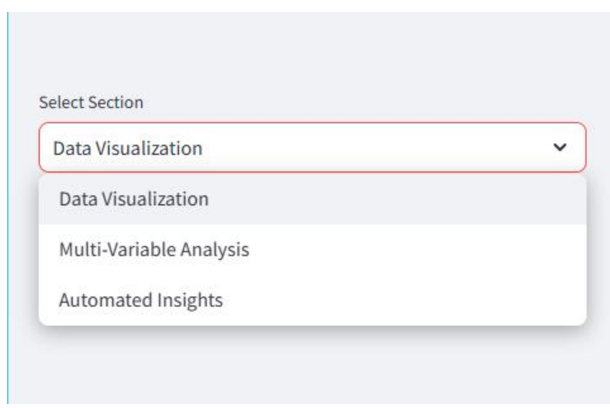


Fig.6. Select section in the system interface.

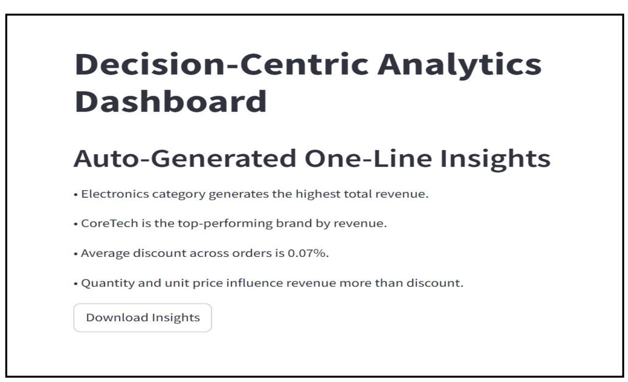


Fig.7. Visualization interface.

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 14 Issue V May 2026- Available at www.ijraset.com

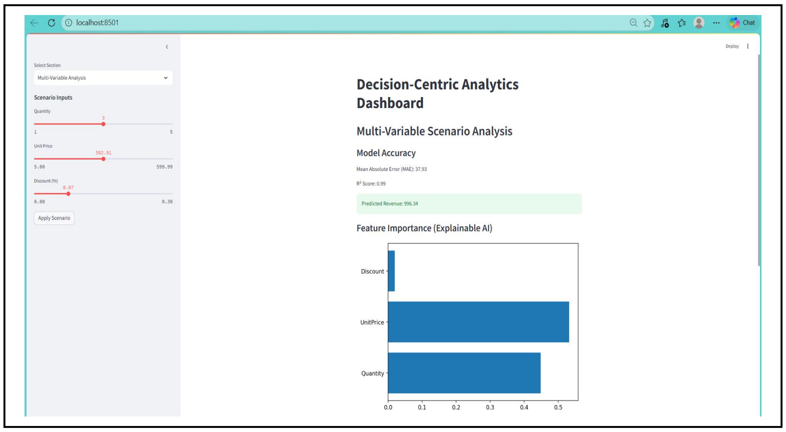


Fig.8. Multi-Variable Analysis interface.

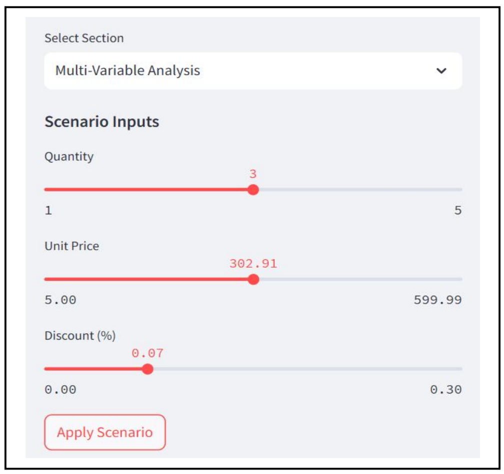


Fig.9. Scenario Inputs for Multi-variable analysis.

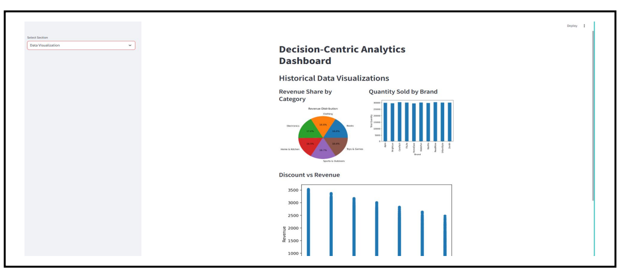


Fig 10. Automated Insights interface.

Fig. 6. shows the select section of the Analytics Dashboard, providing the options to the user, to select the options according to the usage. It has options: Data Visualization, Multi-Variable Analysis and Automated Insights.

Fig 7. Shows the data visualization interface of the system. It shows the pre-defined KPIs, thus provides the high-level summary of business performance with the help of graphs and charts. The visualization for the used transactional dataset focuses on comparisons based on product categories, which will help the decision-makers to quickly compare the current condition of the company in the market.

Fig 8. is the multi-variable analysis interface of the dashboard system. It has the slider as shown in the Fig 9. For inputs. The user can adjust the inputs like, unit price, discount and quantity to predict the change in the revenue.

To support predictive decision-making, Random forest model is used for the prediction. As shown in Fig 10. the performance of the system was evaluated with the help of metrics R^2 and Mean Absolute Error (MAE). As shown in the Table 2, the R^2 score is equal to 0.99. As its closer to 1, this means that the model can capture nearly all variability in the target variable,. This means that the model is fit and stronger. The value of MAE is 37.93. It's a lower value, thus the prediction accuracy is better.

These performance metrics are used internally in the system to validate if the predictive model is reliable by the business users before deploying it for the usage of end users. This design ensures that decision-makers benefit from accurate predictive analytics without needing to interpret technical evaluation measures. This was of prediction based on the basis of multiple factors helps the user to analyze the conditions, understand the importance of each features, and use these insights in future during sudden situations in the business market.

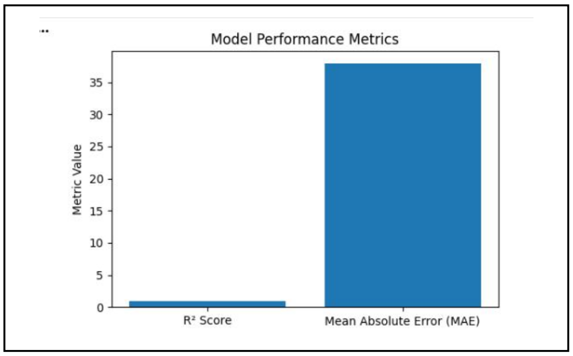


Fig.11. Model Performance Metrics

TABLE II. Model Evaluation Metrcics

Metric	***Value***
R^2 Score	*0.99*
Mean Absolute Error (MAE)	37.93

Fig 10. shows the automated insights generation interface. It directly shows the insights derived from the graphs in the form of simpler lines which can be used to understand the data along with the visualizations. These are easily understandable and readable by anyone. There is an option provided for downloading this insights. The downloaded insights will be stored in the form of .txt file.

Overall, together all components of the proposed system successfully provides an interface for the users, which is time saving, efficient and less complex. The interface of the system can be used by anyone, even from non-technical field as its user-friendly. The decision making and interpreting becomes much simpler with the help of this system.

VI. CONCLUSION

This paper shows a project that implements a decision-based data visualization dashboard, which provides options to generate automated insights and download them for making decisions instead of manually finding them from the visualizations, and also predictions using a machine learning regression algorithm on the basis of multi-variable data, allowing the users to change the values of the variables and see the changes in the revenue accordingly. The prediction model performs well with a R^2 score of 0.99 and MAE score of 37.93.

In the future, the idea can be extended by providing real-time visualization by incorporating the changes in the dataset, also adding various other prediction features, and providing the advanced natural language processed insights. We can also add an explanation for the events that occurred with the help of XAI. Overall, this paper suggests an efficient application for decision-centric data visualization and can also be used for various datasets with some changes.

REFERENCES

[1] Ismael, S. N., & Mohd, O. (2025). Beyond Dashboard: How Ai Shaping Business Intelligence. International Journal of Academic Research in Business and Social Sciences, 15(10), 1295–1303. https://doi.org/10.6007/IJARBSS/v15-i10/26731

[2] Jain, A. M. (2023). AI-Powered Business Intelligence Dashboards : A Cross-Sector analysis of transformative impact and future directions. International Journal of Scientific Research in Computer Science Engineering and Information Technology, 524–536. https://doi.org/10.32628/cseit23564514

[3] Shamnad Mohamed Shaffi. "AI-Driven Analytics: The Future of Business Intelligence." International Journal of Research in Engineering and Science, vol. 12, no. 12, 1 Dec. 2024, pp. 356–367, www.researchgate.net/publication/389554401_AI-Driven_Analytics_The_Future_of_Business_Intelligence.

[4] Cate, M. (2025, January 1). AI-Driven Automation of Big Data Insights for Business Intelligence. https://www.researchgate.net/publication/388415967_AI-Driven_Automation_of_Big_Data_Insights_for_Business_Intelligenc e

[5] Ezeilo, O. J., Orobosa Ikponmwoba, S., Chima, O. K., Ojonugwa, B. M., Ochefu, A., & Adesuyi, M. O. (n.d.). Systematic Review of Business Intelligence Tools and Strategic Dash boarding Techniques. International Journal of Scientific Research in Science and Technology Available Online. https://doi.org/10.32628/IJSRST

[6] J. Ramya, Sai Sahishnu Yerraguravagari, Santosh Gaikwad, Rajeev Kumar Gupta, Kavipragash R (2024) AI and Machine Learning in Predictive Analytics: Revolutionizing Business Strategies through Big Data Insights. Library Progress International, 44(3), 14192-14201

[7] Chen, R. H. Chiang, and V. C. Storey, "Business intelligence and analytics: From big data to big impact," *MIS Quarterly*, vol. 36, no. 4, pp. 1165–1188, 2012.

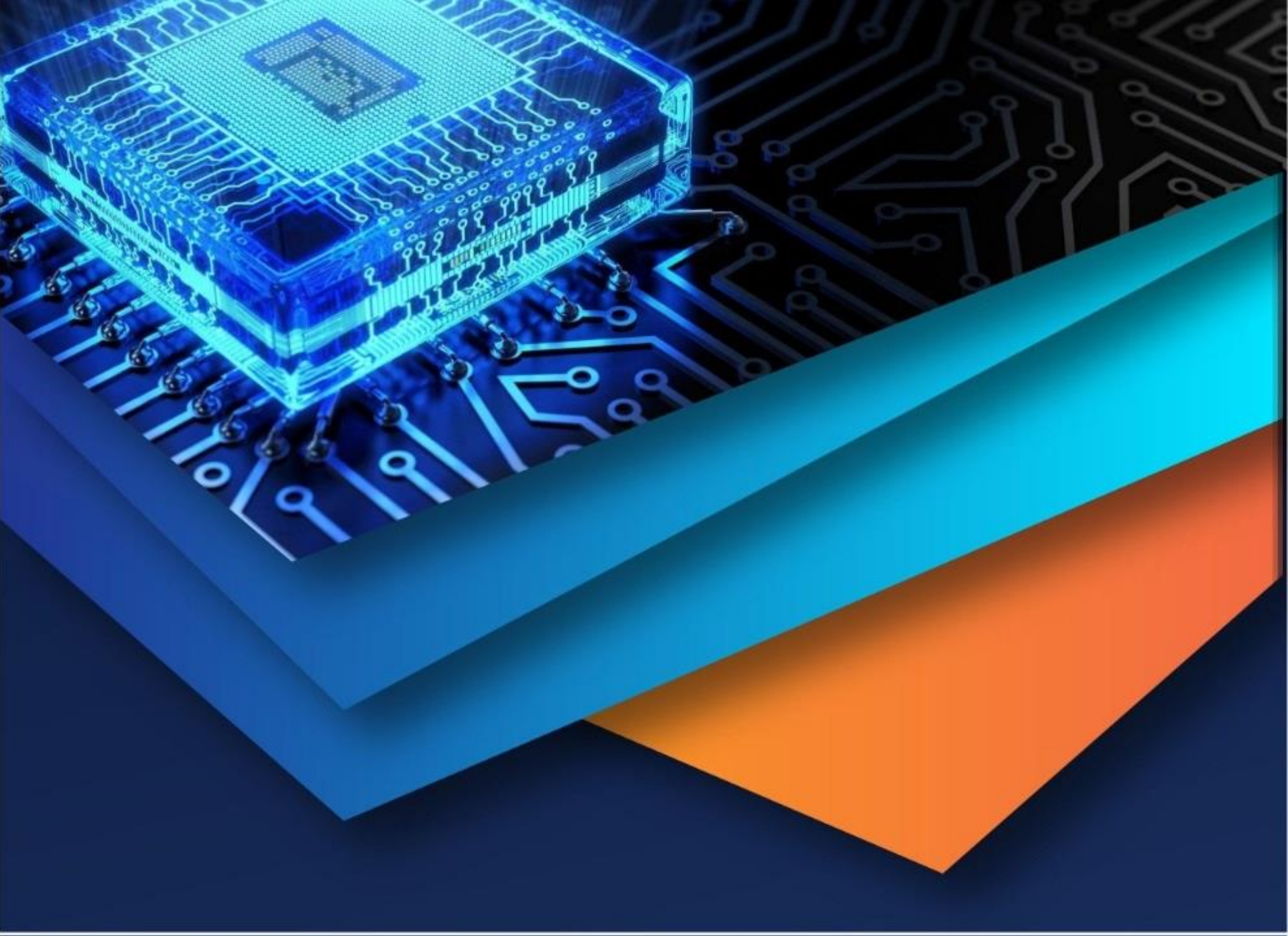
[8] T. Davenport and J. Harris, *Competing on Analytics: The New Science of Winning*, Boston, MA, USA: Harvard Business School Press, 2017.

[9] A. Gandomi and M. Haider, "Beyond the hype: Big data concepts, methods, and analytics," *International Journal of Information Management*, vol. 35, no. 2, pp. 137–144, 2015.

[10] L. Breiman, "Random forests," *Machine Learning*, vol. 45, no. 1, pp. 5–32, 2001.

[11] M. T. Ribeiro, S. Singh, and C. Guestrin, "Why should I trust you? Explaining the predictions of any classifier," in *Proc. ACM SIGKDD Int. Conf. Knowledge Discovery and Data Mining*, 2016, pp. 1135–1144.

[12] F. Provost and T. Fawcett, *Data Science for Business: What You Need to Know about Data Mining and Data-Analytic Thinking*, Sebastopol, CA, USA: O'Reilly Media, 2013.



10.22214/IJRASET

INDEX COPERNICUS

45.98

IMPACT FACTOR: 7.129

TOGETHER WE REACH THE GOAL

IMPACT FACTOR: 7.429

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY