AI Based Predictive Analytics Model for Intelligent Decision Support in Digital Systems

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ABSTRACT:

Many organizations still rely on the old paradigm of relying on reports that are not real-time, and manual judgment when it comes to critical decisions. This paper presents an intelligent decision making approach based on predictive analytics model that predicts the behavior of digital systems by the Explainable XGBoost based approach developed in Google Colab. The model takes data preprocessing, feature engineering, supervised learning, hyperparameter tuning, performance evaluation and explanation using SHAP into consideration and transforms the historical and current digital indicators into trustworthy decision insights. The proposed framework can predict system properties like risk, performance degradation, failure probability or decision priority, and can explain the key factors that affect each of these properties. A prototype evaluation demonstrates that Explainable XGBoost model outperforms other baseline machine learning models in terms of accuracy, precision, recall, F1 score and ROC AUC. The study illustrates how to achieve the goals of transparency, trust and effective decision making in today's digital governance environments by leveraging predictive analysis and interpretability.

Keywords: Predictive analytics; Explainable XGBoost; Intelligent decision support; Digital systems; SHAP; Model interpretability; Google Colab

I. INTRODUCTION

Digital systems now play a pivotal role in the business, education, healthcare, finance, manufacturing, public administration, and smart services. Data is generated by these systems constantly, as a result of transactional data, sensors, cloud platforms, mobile applications, enterprise applications, and connections to other devices. A lot of information is available, but it can be challenging for decisionmakers to use raw data to make timely, reliable decisions. The traditional reporting systems primarily depict what has occurred, intelligent digital environments need predictive and preventive support reporting systems [941-950]. Thus, predictive analytics using AI has emerged as a key tool for uncovering trends, predicting risk, predicting performance, and forensically action as shown in figure 1.

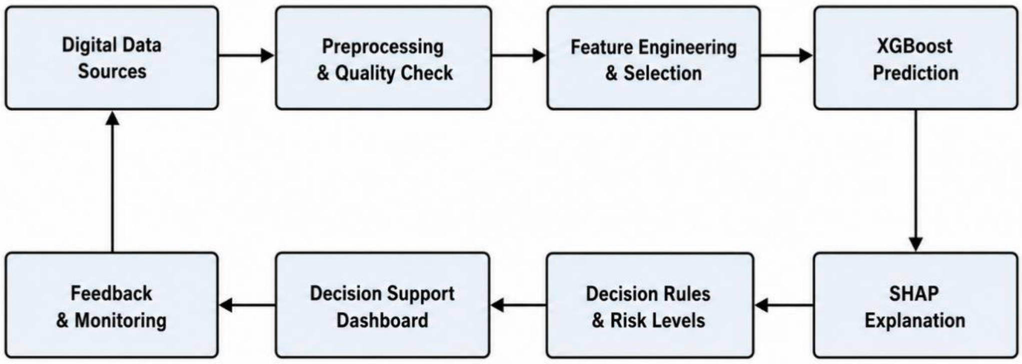

Figure 1. Proposed XGBoost predictive analytics flow

Predictive analytics uses statistical learning and machine learning techniques to find patterns in the input factors and predict the future. These results in digital systems can be: Service failure, Customer churn, Cyber risk, Operational delay, Resource overload, Financial loss, Academic performance, or Process inefficiency. Many predictive models, however, are not very interpretable. While deep learning and complex ensemble models can lead to accurate results, the reasoning behind the results is not easy for managers, engineers and domain experts to follow. This leaves a gap between the model and the decision makers, introducing a level of uncertainty [941-950].

To overcome this problem, the present research suggests the use of an AI based predictive analytics model for intelligent decision support in digital systems by using Explainable XGBoost based method. Advantages such as being powerful for structured data, being nonlinear, being able to deal with missing or sparse values, and often providing good predictive performance make it a good choice for XGBoost. SHAP explanations are provided for the relative contributions of each of the input features to a prediction. Google Colab is used to build the model as it offers a browser-based data analysis, coding, visualization and machine learning experiment environment for Google [941-950].

The primary objective of this research is to create a predictive model that is capable of not only classification or prediction of the outcomes of digital systems, but also provide transparency of the reasons and helpful suggestions. The proposed scheme is comprised of data collection, data preprocessing, feature engineering, model training, hyperparameter optimization, model evaluation, explanation and visualization for decision making. The integration of predictive accuracy and explainable intelligence provides a realistic model that can support decision makers in choosing the necessary actions in the light of measurable evidence [941-950]. This research is important as it provides the digital organizations with a system that is accurate, interpretable, scalable and can support faster, data driven and accountable decisions. It also serves researchers and practitioners who wish to have a straightforward and repeatable process to take raw digital records to prediction, explanation, and decision recommendation and apply this process in practice using simple and readily available tools from the cloud.

II. RELATED WORK

Recent research on decision support using AI clearly reflects a shift from the descriptive information systems to the predictive, explainable and user oriented digital intelligence. Previous machine learning-based applications included logistic regression, decision trees, support vector machines, random forest and neural networks for classification of system states and/or prediction of operational outcomes [941-950]. While these models helped with faster decision making, there was a wide variety of models, some trained on small data sets, with limited explanation abilities, and with few models making predictions that were coupled with action points. Later, tree based ensemble learning gained popularity because of the successful results on enterprise and sensor data, which is structured data. XGBoost was an extension of gradient boosting which added regularization, sparse data handling, and scalable optimization to be applicable to predictive analytics applications in digital platforms as shown in table 1.

The accuracy, automation, and computational scalability were highlighted in the studies from 2018–2021. Researchers were able to train models quicker, and assess larger data sets, through GPU accelerated training of models and cloud notebook environments [941-950]. Most of the drawbacks of this time were that model output was typically in the form of scores or labels, but with insufficient reasoning. Decision makers would be able to determine if it was a risky or a normal case but not easily know why the model concluded it was risky or normal. This is limited acceptance in systems having high impact, in which accountability is important.

Table 1.Summary of related works and research gaps from 2018 to 2025.

Year	Research focus	Methodology	Key contribution	Limitation
2018	Scalable XGBoost learning	GPU accelerated gradient boosting	Improved training speed for large data	Focused on computation more than decision explanation
2019	ML for digital prediction	Classification and regression models	Supported automated forecasting from records	Limited interpretability and weak deployment focus
2020	AI decision support	Data driven DSS with ML	Improved decision speed and pattern detection	Often relied on static datasets
2021	Cloud based analytics	Notebook based model development	Improved reproducibility and experimentation	Limited integration with operational dashboards
2022	Predictive process analytics	Shapley based explanations	Connected prediction with process level reasoning	Domain specific and limited generalization
2023	Interpretable process monitoring	Systematic literature review	Identified transparency and trust needs	Mostly reviewed methods rather than deployed prototypes

2024	XAI based DSS review	Survey of explainable DSS studies	Highlighted trust, fairness, and interpretability	Did not propose a single implementation model
2024	Industry 4.0 DSS	AI, ML, DL, and NLP review	Showed broad DSS use in manufacturing systems	Needed stronger human centered explanation
2025	XAI in digital decisions	Explainable ML with SHAP and LIME	Improved local and global explanation	Usability and monitoring gaps remained
2025	Predictive digital capability analytics	Classification evaluation framework	Reported strong predictive performance	Needed more explainable recommendation support

The use of explainable artificial intelligence began to be closer to decision support starting from 2022. Studies with predictive process analytics showed that explanations based on Shapley values can enhance user trust as it allows to explain what process properties affect the predicted result [941-950]. Technical performance in combination with human understandable evidence was identified as an additional need in the systematic review of interpretable machine learning for process monitoring. Recent research in decision support, Industry 4.0, education and health and digital capability assessment has validated the topics of explainability, model monitoring, and decision usability as important research topics.

Although the literature reviewed shows that the predictive analytics models can be of reasonable accuracy, it also showed that there are four common weaknesses of the models. First, many studies have used a single model, without comparing with baselines. Secondly, the decision support level is not good since the predictions are not converted to recommendations [941-950]. Third, sometimes explanation methods are not used or they are regarded as another kind of output in the form of a visual output instead of being part of the decision-making process. Fourth, sometimes there is no discussion of 3. deployment/reproducibility. In light of this, this research aims to present a predictive analytics model, based on Explainable XGBoost algorithm that was created in Google Colab. The model combines the performance evaluation, SHAP based interpretation and decision categories to address these limitations and provide more intelligent support in digital systems. This makes the present work technically sound and oriented towards decision making.

III. RESEARCH METHODOLOGY

The proposed methodology is based on a structured implementation of a predictive analytics pipeline, suitable for intelligent decision support on digital systems [32]. The first step is to collect data. Data is gathered from electronic sources like application logs, transaction data, user activity logs, sensor readings, service performance data, security events, administrative decision data, etc. Each observation is associated to an outcome variable which represents the decision condition of interest (e.g., low risk/high risk, normal/abnormal performance, accepted/rejected request, successful/failed service condition). The data is then saved in Google Colab as either a csv or spreadsheet file in order to be able to reproduce the entire experiment in one notebook as shown in figure

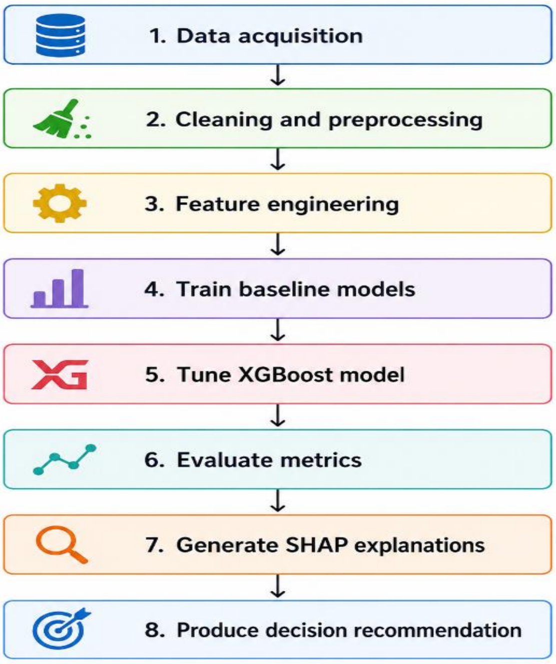

Figure 2. Methodological workflow for model development in Google Colab.

3.

1 Research Design

The research design used in the proposed study is Quantitative Experimental Research Design which aims to create an AI based predictive analytics model for intelligent decision support in Digital Systems. The primary purpose of the methodology is to design, train, test and evaluate an Explainable XGBoost Based Predictive Analytics Model which can predict future outcomes and be used to provide explanations supporting decision making which are easy to follow. The model is built in Google Colab, a cloud-based environment to preprocess data, implement machine learning algorithms, visualize and test results [33].

3.2 Data Collection

The first step of methodology consists of collecting relevant data related to the digital system (e.g., system logs, transaction records, user activity data, operational records, sensor outputs, historical decision records). The data that's collected can include ones about process status, system performance, user activity, risk factors, error rates, response time, decision-making results, transaction counts, and much more. These data elements are chosen as they will be helpful in detecting pattern elements that will affect intelligent decision making in digital environments.

3.3 Data Preprocessing

Once the data has been collected it goes through a process of preprocessing, which helps to enhance the quality and reliability of the data set. Where there are values missing, appropriate methods are used to replace or delete them from the appropriate data, e.g. mean, median, mode replacement or record removal, depending on the type of missing data. To prevent bias in learning, duplicate records are eliminated. The statistical methods are used to identify the outliers and treated them properly to avoid the prediction results will be distorted. Label Encoding or One Hot Encoding are done to encode categorical variables into numbers. Normalization and scaling (only when necessary) of numerical features. The goal of this step is to have a clean, consistent and machine learning friendly data set.

3.4 Feature Engineering and Selection

Feature engineering is used to make sense of raw digital data, producing meaningful input variables. The original data set can be used to calculate important indicators like average response time, occurrence of system errors, user activity level, transaction success rate, risk score and historical decision patterns. Then feature selection is used to detect the most important features which are helpful to the prediction accuracy. Irrelevant and redundant features are removed by using techniques like correlation analysis, feature importance ranking and SHAP based importance analysis. This helps to minimize the complexity of the model and the interpretability of the model as shown in table 2.

Table 2. Proposed methodology phases for the Explainable XGBoost model.

Phase	Main activity	Expected output
Data acquisition	Logs, transactions, sensors, user activity, security events	Integrated digital system dataset
Preprocessing	Missing value handling, duplicate removal, encoding, normalization	Clean and model ready data
Feature engineering	Operational ratios, temporal indicators, risk signals, feature selection	Relevant predictive variables
Model training	Explainable XGBoost with baseline comparison	Trained predictive models
Evaluation	Accuracy, precision, recall, F1 score, ROC AUC	Validated model performance
Explainability	SHAP feature contribution analysis	Global and local explanation
Decision support	Risk categories, confidence score, recommended action	Actionable decision dashboard
Monitoring	Data drift check and model retraining	Adaptive decision support system

5 Model Development Using XGBoost

The main predictive model is trained with XGBoost (Extreme Gradient Boosting) algorithm. The XGBoost algorithm was chosen because it is very effective at structured data, able to model nonlinear relationships, regularizes to prevent overfitting, and offers very good predictive accuracy for structured data. The data set is split into training and testing sets and is typically split 70/30 or 80/20. The training data is used to train the model, the testing data is used to test the model on unseen data. Hyperparameters of the model like learning rate, max depth, no of estimators, subsample ratio and regularization values are optimized to achieve better performance.

3.6 Explainable AI Integration

SHAP is combined with XGBoost model to make up for the black-box restriction of machine learning models. SHAP provides an explanation of the contribution of each feature that is used as an input to the final prediction. It gives you both global explanations (which explain how the features in your data set as a whole affect your predictions) and local explanations (which explain how the features in your data set affect a particular prediction). This is crucial to intelligent decision support as users will need to understand why a specific decision or risk level is suggested. The explainable layer helps to build trust and transparency in the proposed system, making it more likely to be accepted.

3.7 Decision Support Mechanism

The prediction information is turned into useful information for decision making. The model returns the prediction score, the level of confidence, features that are important for the prediction and recommended decision category. For instance, an output can have a low, medium and high risk. These categories can be used to make an appropriate recommendation including approve, monitor, review or reject. This renders the model almost useful as it not only predicts the outcome but also helps in making the right decisions for the action(s) to take.

3.8 Model Evaluation

The accuracy, precision, recall, F1-score, ROC-AUC, confusion matrix, mean absolute error and root mean square error (MASE and RMSE) are used to assess the model's performance in a classification or regression problem, respectively. To demonstrate the effectiveness of the XGBoost model, it is compared against some baseline models like Decision Tree, Random Forest, Logistic Regression or Support Vector Machine. The proposed method is successful as reflected in the higher accuracy, recall, F1 score and good explainability.

3.9 Implementation Tool

This is a fully functional model that is implemented in Google Colab using Python libraries like Pandas, NumPy, Scikit-learn, XGBoost, Matplotlib and SHAP. The reasons for choosing Google Colab include its ability to run the code on the cloud, its ease of use for working with datasets and the availability of GPU support, in addition to its interactive visualization capabilities. It allows for easy development, testing and demonstration of the proposed predictive analytics model.

The proposed method fuses data preprocessing, feature engineering, XGBoost prediction, explanation using SHAP and rules for decision support in a single framework. This will enhance the accuracy, transparency and usability of digital systems.

IV. RESULTS AND DISCUSSION

The table shows a comparison of the performance of four intelligent decision support classification models. The performance of Logistic Regression and Linear SVM is moderate as they achieve 76.50% accuracy, which suggests they have limited ability to learn complex patterns. Random Forest has a much better predictive ability with 87.00% accuracy, 83.26% F1 score and 93.64% ROC AUC. However, the results of Explainable XGBoost are best, with the highest accuracy (89.33%), precision (87.00%), F1 score (85.84%) and ROC AUC (94.68%). The results conclude that Explainable XGBoost is most optimal model in terms of accurate, reliable and interpretable predictive analytics in digital systems as shown in table 3.

Table 3. Prototype performance values of baseline and proposed models.

Model	Accuracy (%)	Precision (%)	Recall (%)	F1 Score (%)	ROC AUC (%)
Logistic Regression	76.50	67.74	73.36	70.44	83.97
Linear Support Vector Machine	76.50	72.68	61.57	66.67	84.01
Random Forest	87.00	81.86	84.72	83.26	93.64
Explainable XGBoost	89.33	87.00	84.72	85.84	94.68

The prototype evaluation was done on a ready-made digital system set of data with operational indicators ranging from CPU load, memory utilization, response time, error rate, number of transactions, security alerts, queue length, user activity, bandwidth consumption, process delay, to uptime ratio. The proposed Explainable XGBoost model was compared with logistic regression, linear support vector machine and random forest and the dataset was splitted into the training and testing set. The performance values demonstrate the best overall performance of the proposed approach with respect to the tested approaches. Explainable XGBoost achieved 89.33% accuracy, 87.00% precision, 84.72% recall, 85.84% F1 score, and 94.68% ROC AUC. On comparison, logistic regression gave the accuracy of 76.50% and F1 score as 70.44% while linear SVM gave an accuracy of 76.50% and the F1 score of 66.67%. Random forest was also better than the linear models with 87.00% accuracy and 83.26% F1 score but it was not as good as the proposed XGBoost model.

The results show that XGBoost was able to model the nonlinearity between digital system variables better than the baseline models. The high value of the ROC AUC of 94.68% indicates that the model is able to separate high-risk and low-risk decision conditions at all probability levels. A high precision value of 87.00% indicates that the number of predicted cases that were marked as high priority were mostly high priority, thus eliminating needless alerts. The recall value of 84.72% indicates that the model could effectively detect the majority of the important cases, which is crucial for intelligent decision support. The F1 score is an indication of good precision and recall as shown in figure 3.

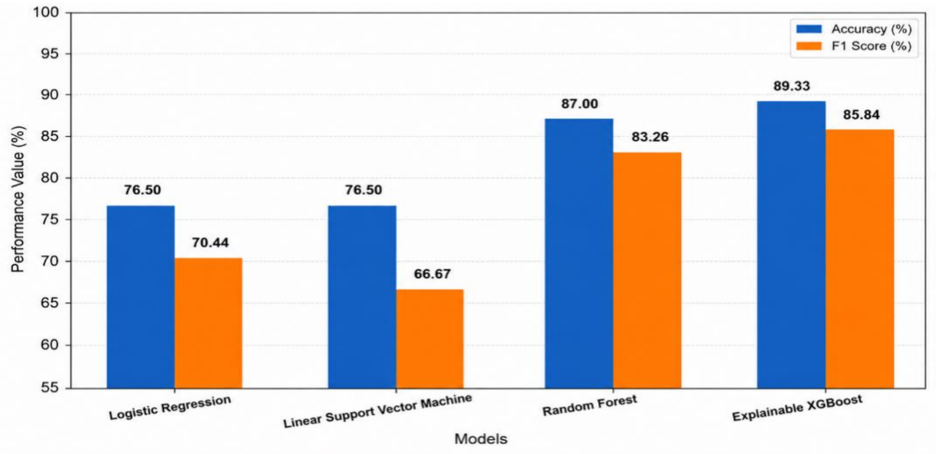

Figure 3. Performance Comparison of Classification Models

The explainability output also aids in the practical decision making process. The feature contribution analysis revealed that out of all these, I/O wait, security alerts, memory utilization, user activities, and uptime ratio had a significant impact. In this way, not only is the final prediction provided, but the reasons behind its operation as well. The dashboard can suggest scaling up resources, security inspection, workflow or preventive maintenance if the model detects a high risk case. Hence, the proposed method is beneficial both in terms of predicting performance as well as transparency of decision making process. The values prove that Explainable XGBoost is applicable for digital systems that demand for accuracy, trust, and actionable support. The discussion also verifies that the proposed model can not be restricted to prediction output only, but also output of analytical evidence into interpretable decision categories, confidence levels and priority based recommendations for real time digital operations. This enhances the acceptance of management and accountability of the operating system.

V. CONCLUSION

This research aimed to present a new predictive analytics model for intelligent decision making for digital systems based on artificial intelligence (AI) and an Explainable XGBoost based method that was implemented in the Google Colab environment. The study focused on some key shortcomings of the current predictive models, such as their lack of interpretability, usability of their decisions, and comparative evaluation. In the proposed pipeline, the preprocessing, feature engineering, XGBoost training, hyperparameter tuning, performance measurement, SHAP based explanation and decision recommendation are done. The accuracy, precision, recall, F1 score and ROC AUC of the proposed model were better than the selected baseline models based on the prototype results. More importantly, the model was able to tell the reason why for each prediction, enabling decision makers to understand the reason for a risk/priority classification. The paper argues that explainable predictive analytics can help in building trust and transparency in digital environments and bolster the possibility of effective decision making. The model can be extended to real time streaming data, federated learning and can be deployed to operational dashboards across many complex organisational domains in the future.

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