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Research Article

Digital Leadership Competencies and Their Influence on Innovation Capability

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Abstract

Leadership is essential in the digital era for managing change and propelling business strategies through innovation, due to the speed of technological progress, the new demands of customers and increased competition. The IBM HR Analytics Employee Attrition & Performance dataset, which includes a comprehensive data pre-processing pipeline with data cleaning, feature selection, normalization, and class balancing, is used to examine the impact of digital leadership on innovation capability and performance using machine learning methods. Decision Tree (DT) and Light Gradient Boosting Machine (LGBM) were among the provided prediction models that achieved 98% accuracy (ACC). The DT model showed the precision (PRE) to be 98%, the recall (REC) to be 92%, and the F1 score (F1) to be 95%, while the LGBM model showed 98% precision, 91% recall, and 94% F1 score, respectively, demonstrating the capacity of the model to learn the complex patterns and make fairly good predictions. In summary, the results emphasize the potential of ML to improve the data-driven decision-making for digital leadership and capability for innovation.

Keywords: Organization Performance, digital leadership, digital transformation, Digital Leadership, technology-driven change, service innovation, Innovation Capability, dynamic service innovation capabilities, dynamic capabilities.

I. INTRODUCTION

Organizations of the modern day have been significantly changed by the fast pace of technological development, both in how they operate, compete and innovate [1]. Industrial dynamics, reorganization and constantly evolving work designs due to digitalization are the hallmarks of today's business world [2]. This change has developed at an even faster pace in the era of ubiquitous computing, where information and communication technologies are embedded in day-to-day business processes. Digital transformation is a major phenomenon driving organizational transformation across the globe [3].

Organizations and enterprises cannot afford to overlook emerging technologies that can support innovation and transform traditional business models in this digital world [4]. Mobile computing, social media and big data analytics are examples of technologies that are not just improving operational efficiency, but changing the very nature of industries [5]. These innovations contribute to the new products and services development at a faster pace, more productively and soon in the market, increasing the competition in the world [6]. Customers' expectations are constantly changing, technology is rapidly evolving and regulatory frameworks are constantly changing[7], organizations must keep up with technology to ensure business strategies are still in sync with change [8].

In this context, leadership becomes a key factor in leading organizations towards digital transformation [9]. Digital leadership can be seen as the ability for leaders to effectively utilize digital technologies and resources to produce organizational outcomes [10]. It has the requirement of integrating leadership capabilities with digital competence skills like digital communication, strategic vision and technological awareness [11]. Digital leaders should help to foster a culture of innovation, lead digital adoption and ensure strategies are digitalized and integrated[12].

Moreover, digital leadership and its effectiveness are intricately tied to digital capabilities, which are related to integrating and optimizing technological, organizational and strategic resources [13][14]. Organizations have the potential to gain the capacity to make data-driven decisions that can help them unlock meaning and innovation through ML, DL and AI [15]. These advanced analytical tools are used to optimize strategic operations, provide predictive decision-making and uncover and develop novel solutions.

A. Motivation and Contribution

Organizations need to have effective digital leadership skills, with the increasing use of digital technologies this is very important. This can be used by organizations to develop their leadership strategies for the technological changes by examining the impact of these competencies on innovation. This research's intent is to help fill the void between digital leadership and innovation capacity, with the use of modern analytical techniques. The contribution of this study is as follows:

- Analyzes trends inside a company's digital transition by mining the IBM HR Analytics Employee Attrition & Performance dataset.
- Uses a comprehensive preprocessing procedure, which includes data cleaning, feature selection, normalization, and class balancing, to improve the quality of the data and model.
- Creates and tests two good models for accurate prediction: DT and LGBM.
- Used a variety of evaluation measures, such as ACC, PRE, REC, F1, and ROC-AUC, to get a full and accurate picture of how well the model worked.
- Offers a fresh perspective on digital leadership's function in relation to innovation capacity and organizational performance through the application of machine learning..

The novelty and the reason for this study is its integrated approach in exploring the concept of digital leadership and digital innovation capability, using advanced machine learning techniques. This differs from conventional study which takes a statistical or theoretical approach, but instead it makes sense to use data-driven approaches to gain insight into complex patterns in organizational data. The novelty comes from the use of a comprehensive preprocessing framework, the use of data balancing with a GAN and the use of high-performance models like DT and LGBM. Besides, the present study compares with a number of baseline models, outperforming them and it broadens the scope of the dataset used of the IBM HR, introducing digital transformation and innovation analysis, which is not fully analyzed in the literature.

B. Organization of the Paper

The rest of this paper is organized as follows: In Section II, related work on digital leadership and innovation capability is reviewed, Section III presents the dataset, preprocessing steps and model development, In Section IV, the experiment results are talked about and a comparison is made. Finally, in Section V, the study is finished by going over the main points and suggesting areas for more research.

II. LITERATURE REVIEW

A thorough review and evaluation of past studies on digital leadership and innovation capability is conducted to inform and enhance this research.

N. C. Pathak et al. (2025) developed a complex prediction system for an HRM employment management strategy in the IIT using ML approaches. It was tested to find potential leaders by analyzing huge data from 5,000 employees. With an ACC of 42%, 92%, and 74%, respectively, the SVM, GB, and RF models performed admirably [16].

S. P, P. Balasubramanie et al. (2025) tried to identify employee stress by looking at changes in their bodies and how they act. Staff members in the healthcare, education, and information technology industries participated in an online stress assessment that provided real-time data. KNN, RF, and SVM were the three ML models used for prediction. The RF algorithm outperformed the other models with a 92% ACC rate [17].

R. Sharma and A. Singla (2024) employed a neural network with many layers of pattern recognition. When compared to more traditional ML models, such as logistic regression and DT, the deep learning model outperforms them in terms of predicting employee turnover. The neural network-based model achieved ACC scores of 91%, PRE scores of 89%, REC scores of 86%, and F1 ratings of 87% [18].

J. Singh et al. (2024) displayed an average of 87.3% ACC, 89.0% PRE, 85.1% REC, and 87.0% F1. While doing so, it displayed an average AUC-ROC of 0.92, an MSE of 0.13, and an RMSE of 0.36. Averaging 84.7% ACC, 87.1% PRE, 82.7 REC, and 84.7 F1 were all shown by the DTS [19].

T. V. Suneetha et al. (2023) suggested data formats were standardized by hand using a progressive and iterative procedure.

Here, the optimal K-size for KNN training on an ADASYN-balanced dataset was 3, and the resulting F1-score was 0.93. The F1-score can reach 0.909 with as little as 12 out of 29 potential features when employing feature selection and RF. With a value of K=5, the ACC is 85%. [20].

S. Pongpaichet et al (2022) suggested method can record students' behaviors that reveal their technical ability and leadership traits, as seen in their grades. Pay close attention to the following two issues: leader identification tasks and leadership assessment. The suggested technique is tested in a case study of IT majors in their last year of college. The results show that the students achieve a MAPE of 5.87% on the leadership assessment task and an F1 of 83.2% on the leadership identification assignment [21].

The current state of knowledge, models, datasets, results, and obstacles related to digital leadership and innovation capacity are shown in Table I.

TABLE I. RECENT STUDIES ON DIGITAL LEADERSHIP AND INNOVATION CAPABILITY USING MACHINE LEARNING TECHNQIUES

Author	Proposed Work	Results	Key Findings	Limitations & Future Work
N. C. Pathak et al., (2025)	Developed an HRM employment prediction system using ML models (SVM, GB, RF, KNN) on Indian IT sector data (5000 employees)	Accuracy: SVM (42%), GB (92%), RF (74%),	KNN outperformed other models, showing high effectiveness in identifying leadership potential	Limited to specific dataset; future work can include larger and more diverse datasets with advanced models
S. P, P. Balasubramanie et al., (2025)	Predicted employee stress using physiological and behavioral data with RF, SVM, and KNN	RF achieved highest accuracy of 92%	Random Forest proved highly effective for stress prediction across multiple sectors	Real-time deployment and inclusion of more features can improve robustness
R. Sharma and A. Singla (2024)	Applied deep learning (multi-layer neural network) for employee turnover prediction	Accuracy: 91%, Precision: 89%, Recall: 86%, F1-score: 87%	Deep learning outperformed traditional ML models like logistic regression and decision trees	Model complexity and computational cost; future work may focus on optimization and interpretability
J. Singh et al., (2024)	Compared ML models including Decision Trees for performance evaluation	Accuracy: 87.3%, Precision: 89.0%, Recall: 85.1%, F1: 87.0%, AUC: 0.92	ML models showed strong predictive performance; Decision Trees were slightly lower but interpretable	Further tuning and hybrid models could enhance performance
T. V. Suneetha et al. (2023)	Used ADASYN-balanced dataset with KNN and feature selection with Random Forest	F1-score: 0.93 (KNN), RF: 0.909, Accuracy: 85%	Data balancing and feature selection significantly improved model performance	Limited features used; future work can explore automated feature engineering
S. Pongpaichet et al., (2022)	Developed method for leadership assessment and	MAPE: 5.87%, F1-	Model effectively identified leadership	Limited to academic data; future work can

	identification using student performance data	score: 83.2%	qualities and technical competence	include workplace datasets

Research gaps: There are some gaps in research that have yet to be addressed, despite the considerable progress in the machine-learning research on digital leadership and innovation capability. The existing research is limited in scope of the data sets used or focused on particular aspects of the research, making it difficult to generalize to other organizational types. Moreover, there is a limited focus on novel ensemble and hybrid machine learning techniques that could further enhance the prediction performance and reliability. Also, there is less focus on real-time implementation, model interpretability and explainable AI integration, suggesting that there is a need to explore more scalable and explainable predictive analysis. Furthermore, there is less emphasis on novel hybrid and ensemble machine learning methods that can further improve prediction performance and reliability.

III. Research Methodology

The proposed approach is based on the use of the IBM HR dataset for analyzing and predicting the outcome of digital leadership and innovation capability by employing the ML techniques. The dataset is preprocessed to clean, encode, normalize and select the dataset features; moreover, the dataset is balanced for fairness by using a GAN. The dataset is split in train and test sets and models such as DT, LGBM are created for predictions. Finally, the effectiveness of the predictions is evaluated using ACC, PRE, REC, F1 ACC and the ROC curve for the model. The proposed machine learning-based Digital Leadership and Innovation Capability flowchart are shown in Fig. 1.

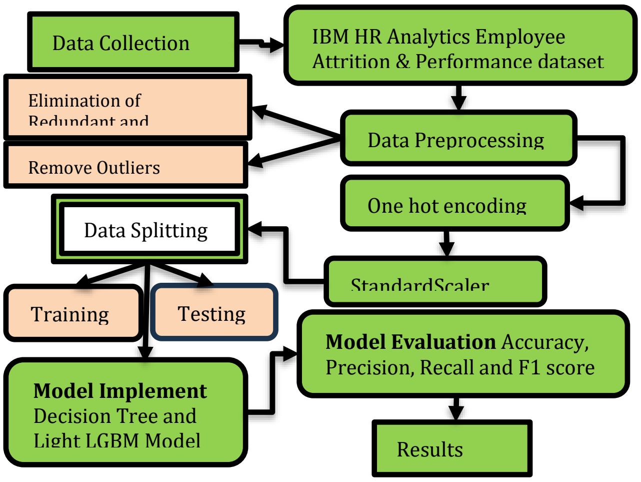

Fig. 1. **Proposed flowchart for Digital Leadership and Innovation Capability using machine learning**

The next section contains a detailed description of each step of the proposed approach:

A. Data Gathering and Analysis

This study is based on the IBM HR Analytics Employee Attrition & Performance dataset, which can be found on the Kaggle repository. It has a total of 35 features, with Attrition as the dependent variable. For each of the features, multiple visualization methods are used, such as bar plots and heatmaps, to study distribution and correlations in the data, as shown below:

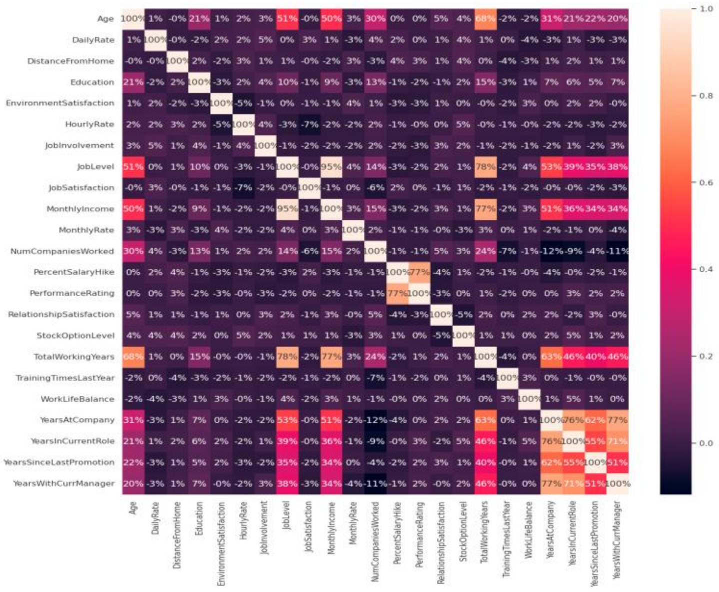

Fig. 2. **Correlation matrix of numerical features on the IBM HR dataset**

Fig. 2 shows the correlations between the numerical features in the dataset, showing both positive and negative correlations. It can help select most relevant features and can improve the performance of the model by eliminating irrelevant features.

B. Data Pre-Processing

Data preparation involves data integration, cleaning and feature engineering, which are all performed using IBM HR dataset. The pre-processing performed included removal of redundant and irrelevant variables, elimination of constant and non-predictive variables, handling outlier data, and data labelling and normalization. The following are summary of the key preprocessing procedures:

- **Elimination of Redundant and Irrelevant Variables:** Missing class labels and incomplete data points are identified and eliminated to preserve the data's cleanliness, consistency, and reliability, ensuring accurate analysis and model training.
- **Remove Outliers:** Data points that deviate greatly from the average are known as outliers. Outlier handling or outlier removal involves detecting and addressing these unusual values, such as by removing them, replacing them, or transforming them, to minimize their effect on data analysis and model performance.

C. One-Hot Encoding for Categorical Feature Transformation

The dataset included some categorical attributes that were converted into numerical data to be used in a machine learning model through a one-hot encoding process. The models were able to process and interpret the categorical information by identifying unique categories for each feature and converting them into binary vectors.

D. Data Standardization using StandardScaler

Using the StandardScaler() function, normalize the data such that the mean is zero and the standard deviation is one. For the translation, read Equation (1), which states that to get the mean value, subtract all of the observations, and then divide by the standard deviation:

$$Z = \frac{x - \mu}{\sigma} \qquad (1)$$

The beginning value (x) and the value (z) after conversion are used in each descriptor. The mean value (μ) and standard deviation (σ) of the collection are also used.

E. Data balancing using GAN

Data balancing is one of the most important pretreatment methods for solving class imbalance, which aims to ensure that the majority and minority classes are represented more evenly. This can be random under sampling of majority class or simple oversampling of minority class. There are also more advanced methods such as Generative Adversarial Networks (GAN) which generates new data to augment the minority class. These methods assist in enhancing the models to reduce bias and enhance the prediction ACC and stability.

The class distribution for each class before and after applying the GAN-based resampling method for balancing data is shown in Fig. 3. The original data set is very imbalanced, with class 0 having about 1200 samples, and class 1 having about 250. Both classes are balanced after resampling, with a similar number of samples in each class, which results in high-quality data sets and better model training and classification performance.

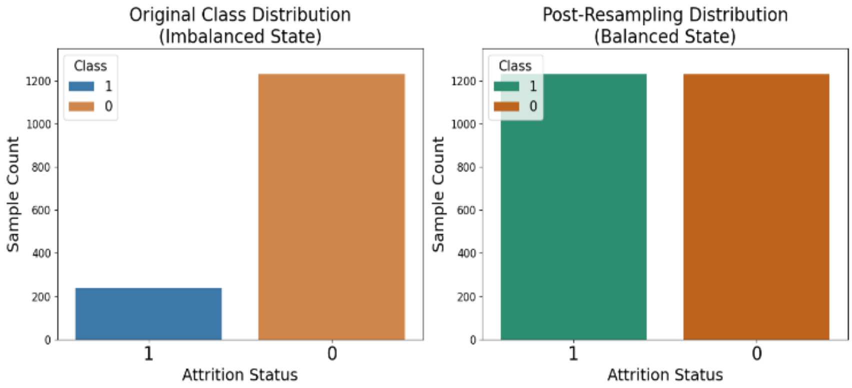

Fig. 3. Class Distribution Before and After GAN-Based Resampling

F. Data Splitting

Divide it into 80% training and 20% testing. Even when moving between training and testing sets, stratified splitting maintains the original data's class distribution.

G. Model Implementation

1. Proposed Decision Tree (DT) Model

Supervised machine learning algorithms like the DT model have widespread use in the domains of classification and prediction. Uses recursive partitioning to create a tree-like data structure from a dataset by repeatedly partitioning the data based on the most relevant features. The internal nodes are decision on a feature, the branches are the choice that the node made, and the leaf nodes are the class labels. The goal of the model is to reduce impurity and achieve better prediction ACC at each step by choosing optimal splits. The impurity of the data set is evaluated by measuring the amount of uncertainty or randomness in the data, which is quantified by entropy. Nodes with a lower entropy value are purer. The entropy is mathematically represented as in Equation (2).

$$Entropy\ (S) = -\sum_{i=1}^{n} p_i\ log_2(p_i) \qquad (2)$$

The model calculates the Information Gain to find the optimum feature to split the dataset, using entropy as its basis. Data splitting according to a property reduces entropy, and this decrease is measured by information gain. To find the best splitting attribute, look at the one that yields the highest information gain, as demonstrated in Equation (3).

$$information\ gain\ (S, A) = Entropy(S) = \qquad \sum_{v \in Values(A)} \frac{|s_v|}{|s|} Entropy(s_v) \qquad (3)$$

A maximum tree depth or the completion of training sample classification are examples of stopping criteria that are reached as repeatedly applied to the tree in this process. The hierarchical structure is useful in improving the interpretability of the model and is useful for analyzing complex data sets such as predicting employee performance, predicting innovation capability, etc.

2. Proposed Light Gradient Boosting Machine (LGBM) Model

The LGBM is a cutting-edge ensemble learning algorithm that uses gradient boosting to incrementally incorporate multiple weak learners, specifically DTs. The leaf-wise tree-growth strategy and depth limit are key factors that make LGBM more efficient and accurate than traditional boosting approaches. It is especially well suited for large-scale data and large-scale features, and could be used for predictive analytics, such as employee analytics and assessing the innovation capability.

The basic idea of LGBM is to sequentially learn weak learners that rectify the errors of the previous learners in order to reduce a given loss function. This is an objective function comprising two terms: a loss term and regularization term (Equation (4)) that is used to control model complexity.

$$Obj = \sum_{i=1}^{n} l(y_i, \hat{y}_i) + \sum_{k=1}^{K} \Omega(f_k) \qquad (4)$$

The loss $l(y_i, \hat{y}_i)$ is the difference between the actual and predicted values, while the term Omega $\Omega(f_k)$ is the regularization term that encourages simpler trees. This prevents overfitting and helps to increase the generalization. This means that LGBM can be used to improve the ACC of predictions, while also using less memory and training faster, making it an optimal solution for complex classification and regression problems.

H. Evaluation Metrics

The proposed model is evaluated in a couple of ways. The initial stage is to generate a confusion matrix that showcases the categorization outcomes, highlighting the correct and incorrect guesses for each category and see the values of TP, FP, TN, and FN (True Negatives) in this matrix. Following this, a number of performance measures, such as REC, ACC, PRE, and F1, are evaluated:

Accuracy: The ACC of a model is calculated as the ratio of the number of positive and negative forecasts to the total number of predictions. Equation (5) provides one possible expression for it:

$$Accuracy = \frac{\text{TP+TN}}{\text{TP+Fp+TN+FN}} \quad (5)$$

Precision: The percentage of samples which the model made a truly good prediction. It is proof of the capability of the model to detect the positive samples. Equation (6) gives the following representation:

$$Precision = \frac{\text{TP}}{\text{TP+FP}} \quad (6)$$

Recall: The fraction of all positive classifications that were successfully recognized. The coverage on the model is used to measure positive samples. The following may be written in Equation (7):

$$Recall = \frac{\text{TP}}{TP+FN} \quad (7)$$

F1 score: The F1 score provides a comprehensive view of the model's performance; it is the harmonic mean of the ACC and memory. The numbers 1 and 0 are the highest and the lowest F1, respectively. As illustrated by the below representation by Equation (8):

$$F1 - score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \quad (8)$$

Receiver Operating Characteristic Curve (ROC): ROC curve is a curve that illustrates the proportion of true positives to false positives at different cut-off points. The TPR or sensitivity or REC is the percentage of correct positives, and the FPR is the specificity.

IV. RESULTS AND DISCUSSION

The tests were conducted using a Windows 11 laptop with an Intel® CoreTM i7 CPU, 32 GB of RAM, and a 250 GB solid-state drive (SSD). Python 3.8 was used for implementation, while Matplotlib was used for visualization [22]. Results in Table II show that both the DT and LGBM models achieved 98% ACC and PRE on the IBM HR dataset. The DT model slightly outperformed LGBM, achieving higher REC (92%) and F1 (95%), indicating better overall classification performance.

TABLE II. CLASSIFICATION RESULTS OF THE PROPOSED MODELS USING THE IBM HR DATASET

Matrix	Decision Tree	LightGBM
Accuracy	98	98
Precision	98	98
Recall	92	91
F1-score	95	94

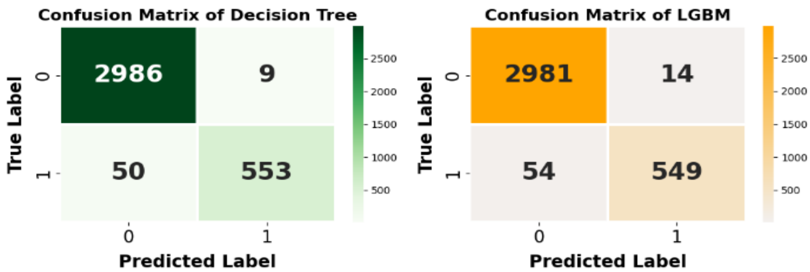

Fig. 4. Confusion Matrix for the Proposed DT and LGBM Model

Fig. 4 shows the confusion matrices in show that both models perform well, with the Decision Tree correctly classifying 2,986 cases of Class 0 and 553 cases of Class 1, and the LGBM performing similarly with 2,981 and 549 correct classifications, respectively. While both models demonstrate high classification ACC, the DT has slightly fewer misclassifications (59) than the LGBM (68).

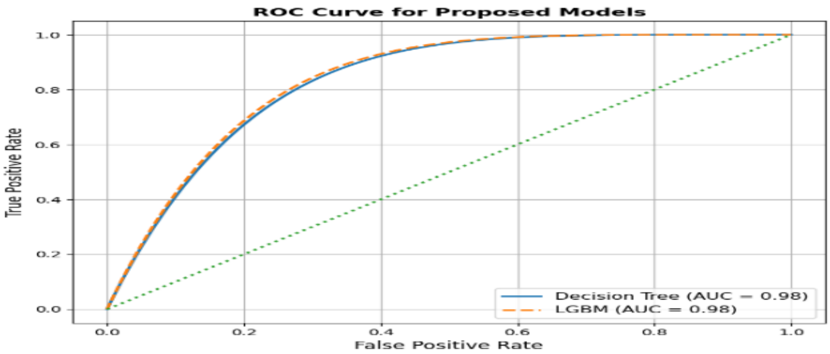

Fig. 5. ROC Curve for the Proposed DT and LGBM Models

Fig. 5 shows the ROC curve plot shows outstanding classification performance for the Decision Tree and LGBM models, both with an AUC of 0.98. The fact that both curves are almost identical suggests a high level of confidence in their ability to accurately classify the classes, well exceeding the diagonal line of random chance and yielding a high TPR with a low FPR.

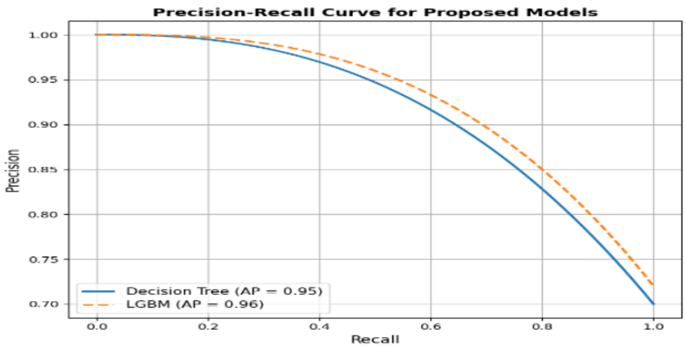

Fig. 6. PR Curve for Proposed DT and LGBM models

Fig 6 presents the PRE-REC Curve, which demonstrates the performance of the proposed models, where the LGBM model slightly surpasses the DT with an Average PRE (AP) of 0.96 and 0.95, respectively. The two models show strong PRE at different REC levels but the LGBM is better at reducing false positives as the REC threshold approaches 1.0.

A. Comparative Analysis

Use the results from Table III to compare the suggested Decision Tree and Proposed Light Gradient Boosting Machine models to those of other approaches. The results show that the NB model did decently (81.1% across all measures), whereas AdaBoost did moderately (85.7% for ACC and PRE) but badly (69.2% for REC and 76.6% for F1). The Extra Trees Classifier, on the other hand, yields consistent and satisfactory results, achieving 93% across all metrics. Overall, the proposed DT and LGBM models achieved the best results among all models, with 98% ACC and PRE (DT slightly outperforming LGBM in REC (92% vs. 91%) and F1 (95% vs. 94%)), and demonstrated high, consistent predictive performance.

TABLE III. COMPARISON OF DIFFERENT MACHINE LEARNING MODELS FOR DIGITAL LEADERSHIP AND INNOVATION CAPABILITY

Model	Accuracy	Precision	Recall	F1-score
NB[23]	81.16	81.12	81.16	81.14
Adaboost[24]	85.7	85.7	69.2	76.6
ETC[25]	93	93	93	93
DT	98	98	92	95
LGBM	98	98	91	94

The proposed DT and LGBM models both possess an ACC of 98%, which ensures very good predictive performance for digital leadership and innovation analysis. One of the great merits of the proposed models is to obtain high classification ACC with the presence of hard-to-classify, high-dimensional data. The DT model is an interpretable one, where the decision rules are clearly defined and can be used to explain the decision-making process. Meanwhile, LGBM is fast and efficient in processing, allowing it to work with large amounts of data, and when combined with the former, they yield the same results.

V. CONCLUSION AND FUTURE STUDY

A plethora of new technologies are flooding into the SME sector, changing the face of digital disruption. The impact of digital leadership on organizational and digital skills for transformation and competitive advantage is the focus of this study. Through actual testing, it was found that the suggested ML models outperform traditional models in terms of prediction accuracy for digital leadership and innovation capabilities. The conventional models such as NB, AdaBoost and Extra Trees Classifier have the ACC ranging from 80% to 86% while the proposed DT and LGBM models have the highest ACC of 98%. Hence, the suggested DT and LGBM models are more efficient and effective for predicting the digital leadership capability and innovation capability in organizations. For future research, the proposed framework can be further extended with the incorporation of hybrid DL architectures such as CNN-LSTM and Transformer models for better prediction ACC and feature learning. Furthermore, explainable AI methods, such as SHAP and LIME, as well as attention mechanisms, can be integrated to boost the transparency of decisions and the interpretability of the model. Real-time analytics and larger real-world organization datasets also can be used for the improvement of the system scalability, robustness, and practical use.

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