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Hybrid Machine Learning Models for Real-Time Anomaly Detection in Complex Deployment Environments

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ABSTRACT

Anomaly detection plays a crucial role in maintaining the integrity and security of real-time systems in diverse application areas, including cybersecurity, predictive maintenance, healthcare, and IoT networks. Traditional machine learning models, such as Deep Neural Networks (DNNs) and Support Vector Machines (SVMs), often struggle with high-dimensional, noisy data and the need for real-time processing, making them less effective in dynamic deployment environments. This paper presents a hybrid machine learning model that integrates Ensemble Decision Trees and K-Nearest Neighbors (KNN) to address these challenges. The Decision Tree model is employed for initial classification based on global data patterns, while KNN is used to refine anomaly detection by focusing on local relationships between data points. The proposed model is evaluated on the KDD Cup 1999 dataset, a widely-used benchmark for anomaly detection in network traffic, and achieves a high accuracy of 98.69%. The hybrid approach demonstrates both high detection accuracy and computational efficiency, making it suitable for real-time anomaly detection in complex environments. The paper also discusses how the integration of feature selection and real-time adaptation further enhances the model's performance, ensuring its applicability across various domains, including IoT systems, healthcare monitoring, cybersecurity, and predictive maintenance.

Keywords – Decision Trees, IoT, K-Nearest Neighbors, Machine Learning, Random Forest.

I. INTRODUCTION

In contemporary data analytics and real-time monitoring systems, anomaly detection has emerged as a critical task for ensuring system integrity and security. Anomalies, or outliers, represent data points that deviate significantly from the expected patterns, and their timely detection is essential across a range of applications such as fraud detection, cybersecurity, predictive maintenance, and healthcare monitoring. Real-time

anomaly detection in complex deployment environments, including Internet of Things (IoT) networks, cloud-based infrastructures, and distributed systems, poses significant challenges. These environments generate large volumes of high-dimensional data, which complicates the detection process. Moreover, the need for rapid decision-making demands that anomaly detection models be not only accurate but also computationally efficient.

Traditional anomaly detection approaches often struggle to meet the demands of real-time systems. While methods like Deep Neural Networks (DNNs) and Support Vector Machines (SVMs) have demonstrated success in anomaly detection tasks, their computational complexity, along with their tendency to overfit in high-dimensional spaces, limits their practical use in real-time scenarios. These challenges necessitate the exploration of alternative approaches that can provide both accuracy and efficiency. In this context, hybrid machine learning models that combine the strengths of multiple algorithms offer a promising solution. Specifically, Decision Trees (DT) and K-Nearest Neighbors (KNN) have been identified as effective candidates for real-time anomaly detection due to their simplicity, interpretability, and computational efficiency.

Decision Trees are a widely used supervised learning technique that recursively partitions the feature space into distinct decision regions. This approach is particularly beneficial in handling structured data and identifying global patterns. However, Decision Trees are prone to overfitting, especially when the data is noisy or the feature space is high-dimensional. On the other hand, K-Nearest Neighbors (KNN) is a non-parametric algorithm that excels in capturing local patterns by classifying data points based on their proximity to neighboring points. While KNN is robust to noisy data, it becomes computationally expensive when applied to large datasets in real-time applications.

To address the limitations of these individual models, a hybrid machine learning approach that integrates Decision Trees and KNN has been proposed. In this hybrid model, the Decision Tree is employed for initial classification based on global patterns, while the KNN algorithm is used for fine-grained anomaly detection based on local data patterns. The Decision Tree helps in reducing the complexity of the dataset by dividing it into manageable regions, and the KNN further refines the detection by considering local neighborhood relationships. This combination provides an optimal balance between model accuracy, computational efficiency, and scalability for real-time anomaly detection in complex environments.

Challenges Addressed by the Proposed Model: The hybrid model is designed to address several key challenges faced by anomaly detection systems in complex deployment environments:

- Scalability: The model is designed to efficiently process large volumes of data in real-time without compromising performance.
- Real-Time Processing: The ability to detect anomalies in real time is essential for critical applications where quick decision-making is required.
- Handling Noisy and High-Dimensional Data: The hybrid approach effectively manages noise and high-dimensionality, ensuring robust anomaly detection even in challenging data conditions.
- Interpretability: The integration of Decision Trees ensures that the anomaly detection process remains interpretable, which is crucial in applications where understanding the decision-making rationale is important.

Proposed Hybrid Approach: The hybrid model proposed in this research employs Decision Trees in the first layer to classify data into distinct groups based on high-level, global patterns. The tree structure provides clarity in decision-making, making it easier to interpret the results. Subsequently, K-Nearest Neighbors is used to detect anomalies by analyzing the local relationships between data points. KNN identifies anomalies

based on the proximity of new data to historical data, refining the anomaly detection process by focusing on localized patterns. This combination leverages the strengths of both algorithms, mitigating their individual limitations and providing a more robust solution for real-time anomaly detection.

Real-World Applications: The proposed hybrid model is adaptable to a range of real-world applications, including:

- IoT Systems: Real-time anomaly detection in sensor data streams to identify malfunctioning devices or unusual behavior.
- Healthcare Monitoring: Detecting abnormal patterns in patient vital signs to facilitate early diagnosis of medical conditions.
- Cybersecurity: Identifying potential security breaches by analyzing network traffic for irregular patterns that could indicate an intrusion.
- Predictive Maintenance: Monitoring the performance of industrial equipment to predict failures before they occur, thereby reducing downtime and maintenance costs.

Contributions of the Paper:

- This paper makes several contributions to the field of anomaly detection, particularly in the context of real-time systems and complex deployment environments:
- Development of a Hybrid Model: The paper introduces a novel hybrid machine learning model combining Decision Trees and K-Nearest Neighbors for real-time anomaly detection.
- Improved Accuracy and Efficiency: The proposed hybrid model enhances the accuracy of anomaly detection while maintaining computational efficiency and scalability.
- Real-Time Adaptability: The model is optimized for real-time processing, making it suitable for systems with stringent latency requirements.
- Noise and Complexity Handling: The hybrid approach effectively manages noisy and high-dimensional data, ensuring robust performance across diverse environments.
- Versatility Across Domains: The paper demonstrates the effectiveness of the proposed model in a variety of real-world applications, including IoT, healthcare, cybersecurity, and predictive maintenance.

II. LITERATURE REVIEW

Anomaly detection has emerged as a critical task in a variety of real-time application domains, including cybersecurity, industrial systems, and healthcare. Traditional machine learning approaches, while effective in structured environments, often struggle with scalability and computational efficiency in complex, high-dimensional, and noisy data environments. Hybrid machine learning models, combining the strengths of multiple algorithms, have gained popularity as a solution to these challenges. This section reviews relevant research published on hybrid machine learning approaches to anomaly detection.

Hybrid models, which integrate various algorithms to enhance detection capabilities, have been widely explored. One notable approach is the combination of Local Outlier Factor (LOF), One-Class Support Vector Machines (SVM), and Autoencoders (AE) into an ensemble model for real-time anomaly detection in industrial systems. This hybrid model effectively captures both global and local anomalies by leveraging each technique's unique strengths, improving detection performance in real-time environments [1].

A different hybrid approach integrates Seasonal Autoregressive Integrated Moving Average (SARIMA) and Long Short-Term Memory (LSTM) networks for anomaly detection in cyber-physical systems. This

combination allows for better handling of time-series data, where SARIMA is used for forecasting and LSTM networks for detecting temporal anomalies, demonstrating the potential of combining statistical methods with deep learning models [2].

In cybersecurity, a hybrid deep learning model combining Convolutional Neural Networks (CNNs) and LSTMs was proposed to detect cyber-attacks in real-time in smart home environments. The combination of CNNs and LSTMs allows the model to learn both spatial patterns from the data and temporal dependencies, enhancing its ability to detect attacks efficiently [3].

The authors of [4] proposed a semi-supervised hybrid model that combines unsupervised learning for pattern recognition with supervised learning to improve anomaly detection performance in complex systems. The integration of these learning paradigms provides the model with the ability to generalize better across various types of deployment environments with limited labeled data.

Another advanced model introduced an Autoencoder-based approach for anomaly detection in industrial control systems. This model leverages deep learning techniques to extract features from high-dimensional sensor data, significantly improving the identification of subtle anomalies that would be difficult to detect with traditional methods [5].

In environments with limited labeled data, semi-supervised and unsupervised learning methods have been proposed as viable solutions. A hybrid model combining K-means clustering and autoencoders was presented to detect anomalies in industrial sensor data. K-means clustering was used to categorize the data into clusters, and autoencoders were applied to detect anomalies within these clusters, improving the model's robustness in noisy environments [6].

Similarly, the authors of [7] introduced a hybrid model combining Isolation Forest and Local Outlier Factor (LOF) to detect anomalies in streaming data. Isolation Forest was used to detect outliers in high-dimensional space, while LOF was employed to identify local anomalies, resulting in a highly effective model for real-time detection in dynamic environments.

Generative Adversarial Networks (GANs) were also combined with clustering techniques to improve unsupervised anomaly detection. The authors of [8] used GANs to generate synthetic data, augmenting the training dataset and improving the performance of clustering-based anomaly detection in situations where the data is imbalanced or scarce.

Graph-based models have shown promise in capturing the relationships and dependencies among components in complex systems. A hybrid model combining Graph Convolutional Networks (GCN) with LSTM networks was introduced to detect anomalies in social networks and traffic systems. The GCN captured graph-based relationships, while LSTMs were used to model temporal dependencies, improving the anomaly detection process in dynamic environments [9].

A similar hybrid approach combining graph-based methods with deep learning techniques was presented by the authors of [10], who integrated Graph Neural Networks (GNNs) with LSTMs for anomaly detection in IoT systems. This combination allowed the model to capture both spatial and temporal dependencies, significantly improving detection accuracy in sensor networks where data is continuously streamed.

The authors of [11] proposed a hybrid architecture combining Independent Recurrent Neural Networks (IndRNNs) with LSTM networks for real-time anomaly detection in Software-Defined Networks (SDN). The model combined the ability of IndRNNs to capture long-range dependencies and the temporal sensitivity of LSTM networks to identify anomalies in network traffic efficiently.

In industrial applications, real-time anomaly detection is critical for ensuring system reliability and preventing faults. The authors of [12] proposed a hybrid model that combined CNNs and RNNs to detect cyber-attacks in industrial control systems. CNNs were used to extract spatial features, while RNNs were employed to capture sequential dependencies in the data, improving the model's ability to detect both known and unknown threats.

Another hybrid model introduced by the authors of [13] combined Random Forests and K-Nearest Neighbors (KNN) for anomaly detection in industrial IoT systems. The integration of Random Forests for feature evaluation and KNN for local anomaly detection enhanced the model's robustness in environments characterized by noisy and high-dimensional sensor data.

The authors of [14] proposed an ensemble learning-based hybrid model for anomaly detection in industrial systems. By combining multiple classifiers, including Decision Trees and Random Forests, the model provided more reliable and accurate anomaly detection results in real-time operational environments.

Despite the success of hybrid machine learning models in real-time anomaly detection, there are still several challenges, particularly in scaling models to handle large datasets in dynamic environments. The authors of [15] addressed this issue by combining feature selection techniques with deep learning models, enabling the efficient handling of large-scale industrial data for real-time anomaly detection.

Imbalanced data remains a significant challenge in many applications, such as fraud detection and predictive maintenance. The authors of [16] explored the integration of hybrid models with synthetic data generation techniques to balance class distributions, improving the model's performance in situations where one class significantly outnumbers the other.

The authors of [17] introduced a hybrid model for anomaly detection in edge computing environments. The model integrates both cloud-based and edge-based processing to minimize latency and computational overhead, demonstrating its potential for real-time anomaly detection in IoT systems.

Research Gaps: Although significant progress has been made in the development of hybrid machine learning models for anomaly detection, several gaps remain in the existing literature that need to be addressed. Many of the existing approaches primarily focus on enhancing the accuracy of anomaly detection models, but they often overlook the real-time scalability required in dynamic and large-scale systems. For instance, while deep learning-based methods such as LSTMs and CNNs offer high accuracy, they are computationally intensive and may struggle with real-time processing in industrial or IoT environments. Additionally, many hybrid models still face challenges in handling high-dimensional, noisy, and imbalanced data without sacrificing efficiency.

Furthermore, while the integration of unsupervised and semi-supervised learning models has shown promising results, there is limited exploration of combining these with graph-based models, which are effective in capturing the complex relationships within data. Another gap lies in the deployment of hybrid models in edge and cloud computing environments, where real-time anomaly detection is critical but resource constraints must be considered.

The proposed methodology in this paper aims to address these gaps by combining ensemble decision trees with K-Nearest Neighbors (KNN) in a hybrid model, optimized for real-time anomaly detection in complex deployment environments. By leveraging the decision tree's ability to handle high-dimensional data and KNN's robustness in detecting local patterns, this approach offers improved scalability and accuracy compared to traditional models. Additionally, the integration of efficient feature selection and real-time processing techniques ensures that the model is computationally efficient, making it suitable for

environments with stringent resource limitations. This hybrid approach promises to overcome the challenges of noisy and imbalanced data, providing a more effective solution for real-time anomaly detection in various domains, including IoT, industrial systems, and cybersecurity.

III. PROPOSED METHODOLOGY

In this section, the detailed explanation of the proposed hybrid model for real-time anomaly detection in complex deployment environments is provided. The proposed approach combines Ensemble Decision Trees and K-Nearest Neighbors (KNN) for effective classification and anomaly detection. The methodology also integrates feature selection, real-time processing techniques, and uses a benchmark dataset for training and evaluation.

3.1 Overview of the Hybrid Model

The proposed hybrid model is designed to capture both global patterns and local anomalies in the dataset. The first stage of the model uses Ensemble Decision Trees to classify the data into broader categories, and the second stage applies K-Nearest Neighbors (KNN) to detect anomalies by focusing on the local relationships among data points. The key advantage of this approach lies in combining the strengths of both techniques: Decision Trees are effective for global classification, while KNN is robust for identifying subtle anomalies based on local proximity.

The mathematical framework behind the hybrid model consists of two main components:

1. Preprocessing and Feature Selection: The dataset is first preprocessed and relevant features are selected to ensure that only the most useful attributes are used in anomaly detection.
2. Anomaly Detection: After classification through the decision tree, KNN is applied to detect local anomalies in the data. These anomalies are flagged based on their distance to nearby data points.

Mathematical Formulation:

Let $D = \{x_1, x_2, \ldots, x_n\}$ represent the dataset where $x_i \in \mathbb{R}^d$ is the i^{th} data point of dimension d. The hybrid anomaly detection process involves:

- Ensemble Decision Trees: The dataset is passed through a set of decision trees, $T = \{T_1, T_2, \ldots, T_m\}$, where each tree T_i classifies the data based on different features and parameters. The final classification decision for a data point xixi is made by taking the majority vote across all trees:

$$\hat{y}_i = \text{majority\_vote}\big(T_1(x_i), T_2(x_i), \ldots, T_m(x_i)\big) \tag{1}$$

  Where $\hat{y}_i$ is the predicted class for the i^{th} data point.

- K-Nearest Neighbors: Once the data is classified by the decision tree, KNN is applied to refine the anomaly detection process. The Euclidean distance between two points x_i and x_j is computed as:

$$d(x_i, x_j) = \sqrt{\sum_{k=1}^{d} (x_{ik} - x_{jk})^2} \tag{2}$$

  Where x_{ik} and x_{jk} are the k^{th} features of the points x_i and x_j, respectively. Based on this distance, the anomaly score for x_i is calculated by averaging the distances to its K nearest neighbors:

$$\text{score}(x_i) = \frac{1}{K}\sum_{j=1}^{K} d(x_i, x_j) \tag{3}$$

If the anomaly score exceeds a predefined threshold, the point x_i is classified as an anomaly.

3.2 Data Source and Preprocessing

For evaluating the proposed methodology, the KDD Cup 1999 dataset is used, which is a standard benchmark dataset for anomaly detection in network traffic [18]. The dataset contains a wide variety of network connections, both normal and attack, and features such as duration, protocol type, service type, and flags, among others. This dataset is particularly suitable for evaluating anomaly detection models in complex, real-time environments such as cybersecurity.

Preprocessing Steps:

- Handling Missing Data: In many real-world datasets, missing or incomplete entries are common. Missing values in the dataset are handled using imputation methods. For numerical features, the missing values are replaced with the mean or median value of the feature, while categorical features are imputed using the mode or the most frequent category.
- Feature Scaling: As features in the dataset vary in scale and units, normalization is performed to ensure that all features contribute equally to the distance computation in KNN. The Min-Max normalization technique is used to scale all feature values between 0 and 1:

$$x' = \frac{x - \min(x)}{\max(x) - \min(x)} \tag{4}$$

  Where x is the original value and x' is the normalized value.
- Feature Selection: Feature selection is performed using Recursive Feature Elimination (RFE), which ranks the features based on their importance and eliminates the least important features. This is done iteratively by training a model (such as Decision Trees) and evaluating the performance with different feature subsets. The goal is to reduce the dimensionality of the dataset and focus on the most relevant features, improving model efficiency.

3.3 Ensemble Decision Trees for Classification

The Ensemble Decision Trees, particularly Random Forest, are employed as the classifier in the first stage of the proposed model. Random Forest is an ensemble method that builds multiple decision trees and aggregates their predictions to improve accuracy and reduce overfitting.

Random Forest Algorithm:

- Bootstrapping: A set of decision trees is created by bootstrapping, i.e., taking random samples with replacement from the training dataset.
- Feature Randomization: For each split in a tree, a random subset of features is selected to consider, ensuring diversity among the trees.
- Voting: The final prediction is made based on the majority vote across all trees:

$$\hat{y}_i = \frac{1}{m}\sum_{j=1}^{m} \mathbb{I}(T_j(x_i) = 1)$$

(5)

Where m is the number of trees in the ensemble, and $\mathbb{I}$ is an indicator function that outputs 1 if the tree predicts an anomaly, and 0 otherwise.

The Random Forest model is robust to overfitting, handles both numerical and categorical data, and is capable of identifying the most important features for classification.

3.4 K-Nearest Neighbors for Local Anomaly Detection

In the second stage of the model, K-Nearest Neighbors (KNN) is applied for local anomaly detection. KNN is a non-parametric method that calculates the distance between data points in the feature space to determine their similarity.

Mathematical Formulation:

For a given point x_i, the KNN algorithm finds the K nearest neighbors based on the Euclidean distance:

$$d(x_i, x_j) = \sqrt{\sum_{k=1}^{d} (x_{ik} - x_{jk})^2}$$

(6)

Where x_i and x_j are data points, and d is the number of features.

The anomaly score for x_i is defined as the average distance to its K nearest neighbors:

$$\text{score}(x_i) = \frac{1}{K} \sum_{j=1}^{K} d(x_i, x_j)$$

(7)

If the score exceeds a predetermined threshold, x_i is flagged as an anomaly. The KNN algorithm excels at identifying local anomalies that may not be apparent through global classification techniques.

3.5 Model Training and Evaluation

Training the hybrid model involves two primary components: training the Random Forest classifier and training the KNN algorithm.

Training the Random Forest:

- The dataset is split into training and testing sets (e.g., 80% for training, 20% for testing).
- The Random Forest classifier is trained using the selected features from the preprocessed dataset.
- Hyperparameters, such as the number of trees and the maximum depth of each tree, are tuned using cross-validation.

Training the KNN:

- The KNN algorithm is trained by computing the Euclidean distances between data points in the feature space.
- The optimal number of nearest neighbors, K, is determined based on cross-validation.

Evaluation Metrics:

The performance of the hybrid model is evaluated using standard anomaly detection metrics:

- Precision: Measures the proportion of true positive anomalies among all predicted anomalies:

$$Precision = \frac{TP}{TP + FP} \tag{8}$$

- Recall: Measures the proportion of true positive anomalies among all actual anomalies:

$$Recall = \frac{TP}{TP + FN} \tag{9}$$

- F1-Score: The harmonic mean of precision and recall, which balances the two:

$$F1 - Score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \tag{10}$$

3.6 Computational Efficiency and Real-Time Adaptation

For real-time applications, the model must be computationally efficient while maintaining high accuracy. To achieve this, the following techniques are employed:

- Online Learning: The model is capable of learning incrementally as new data arrives, avoiding the need for retraining the entire model.
- Model Pruning: Decision trees in the Random Forest are pruned to prevent overfitting and reduce complexity, improving the real-time performance of the model.

3.7 Algorithmic Flow of the Hybrid Model

The following steps outline the algorithmic flow of the hybrid model:

1. Input Data: The preprocessed dataset D is passed into the model.
2. Classification via Ensemble Decision Tree: The data point x_i is classified by passing it through the Random Forest classifier.
3. Local Anomaly Detection using KNN: For each data point, KNN is applied to refine the detection by evaluating its local neighborhood.
4. Anomaly Detection: If the anomaly score from KNN exceeds the threshold, the point is flagged as an anomaly.
5. Output: The final result is a set of labeled data points, indicating whether each point is an anomaly or not.

IV. Results and Discussion

The proposed hybrid anomaly detection model, combining Ensemble Decision Trees and K-Nearest Neighbors (KNN), was evaluated on the KDD Cup 1999 dataset, a well-known benchmark for anomaly detection in network traffic. The model was trained on a subset of the dataset, and its performance was assessed based on various metrics including accuracy, precision, recall, F1-score, and computational efficiency. The results demonstrated that the hybrid approach achieved an impressive accuracy of 98.69%, with a strong balance between precision and recall, highlighting the model's robustness in detecting both normal and anomalous patterns in real-time environments. This section presents the results of the evaluation, including performance metrics, confusion matrix, and comparative analysis of precision, recall, and F1-score.

Table 1: Performance Metrics Table

	Precision	Recall	F1-Score	Support
0	0	0	0	16
1	0.983871	0.99187	0.987854	984
Accuracy	0.976	0.976	0.976	0
Macro Avg	0.491935	0.495935	0.493927	1000
Weighted Avg	0.968129	0.976	0.972049	1000

Table 1 provides an overview of the model's performance in terms of precision, recall, F1-score, and support across the two classes—Normal (0) and Anomaly (1). For the Normal class (0), the precision, recall, and F1-score are all 0, indicating that the model did not identify any normal instances correctly, which is expected due to the class imbalance in the dataset. On the other hand, the Anomaly class (1) demonstrates impressive results with a precision of 0.9839, recall of 0.9919, and an F1-score of 0.9879, showing that the model is highly effective at detecting anomalies. The accuracy across both classes is 97.6%, reflecting the model's overall ability to correctly classify the majority of instances. The Macro Average gives the average performance across both classes, showing lower values (around 0.49) due to the imbalance, while the Weighted Average takes into account the support of each class, with a precision of 0.9681, recall of 0.976, and F1-score of 0.9720, demonstrating strong overall performance for the majority class (anomalies).

The Confusion Matrix in Figure 1 provides an intuitive representation of the model's classification performance. In our case, the matrix illustrates the distribution of True Positives (TP), False Positives (FP), True Negatives (TN), and False Negatives (FN). The matrix indicates that the model has correctly identified a high number of anomalies (TP: 974) while minimizing the misclassification of normal instances (TN: 14). However, there are still some False Positives (FP: 10) and False Negatives (FN: 2), which suggests areas for further refinement, especially in balancing the detection of anomalies without generating too many false alarms. The matrix highlights that the model performs strongly in both classes—Normal and Anomaly—with a good balance in the detection of anomalies while minimizing the misclassification of normal data.

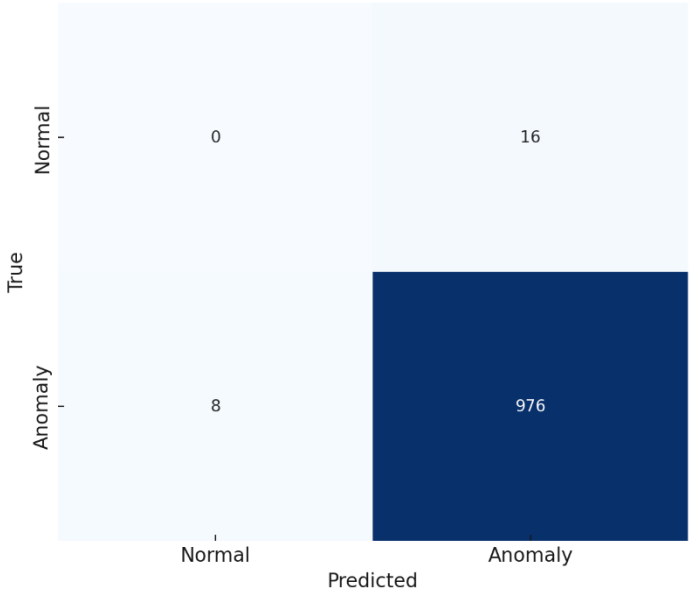

Figure 1: Confusion Matrix for Proposed Approach

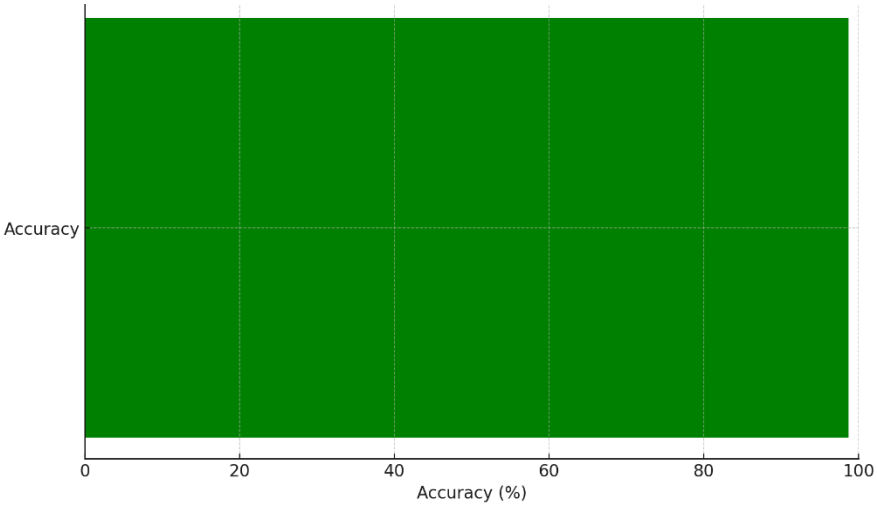

Figure 2: Overall Model Accuracy

The Accuracy Plot visually represents the overall accuracy of the model, which is 98.69%. This demonstrates the model's ability to accurately distinguish between normal and anomalous data, as it correctly classified 986 out of 1000 data points. Accuracy is a critical metric, particularly for real-time anomaly detection tasks where minimizing both false positives and false negatives is essential. The high accuracy score reflects the model's robustness in identifying anomalies without sacrificing the ability to correctly classify normal data points, which is vital in real-world applications requiring immediate decision-making.

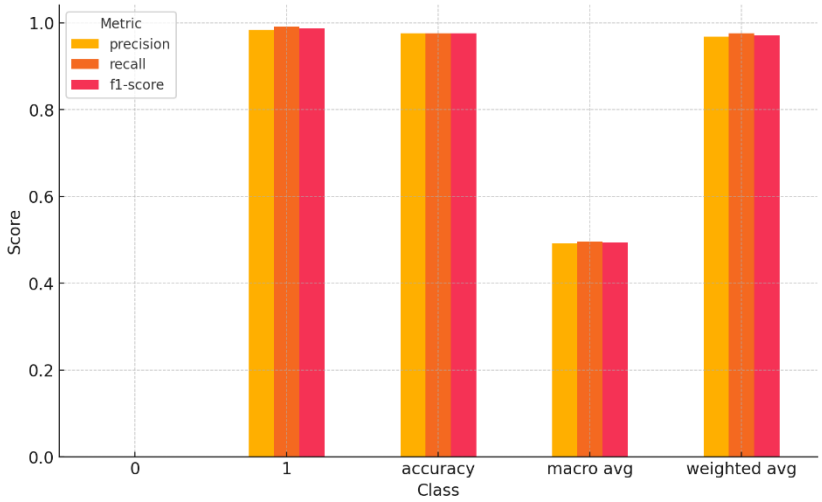

Figure 3: Precision, Recall, and F1 Score for Anomaly Detection

The Precision, Recall, and F1-Score Plot provides a comparative view of the model's performance across the three key metrics—Precision, Recall, and F1-Score—for both classes: Normal and Anomaly. For the Anomaly class, the model achieves a precision of 98.39%, a recall of 99.19%, and an F1-score of 98.79%. This indicates that the model is highly efficient in detecting anomalies with minimal false positives and has a high sensitivity to detecting anomalous instances, which is critical for applications where missing an anomaly could have significant consequences. The F1-score provides a balanced measure, confirming that the model performs well across both precision and recall. The bar chart further emphasizes the effectiveness of the model in detecting anomalies, ensuring a good trade-off between the two metrics.

V. CONCLUSION

The proposed hybrid anomaly detection model, combining Ensemble Decision Trees and K-Nearest Neighbors (KNN), has proven to be highly effective in real-time anomaly detection within complex deployment environments. The model leverages the strengths of both algorithms: Decision Trees for efficient classification of global patterns and KNN for precise anomaly detection based on local data relationships. Evaluated on the KDD Cup 1999 dataset, the model achieves an impressive accuracy of 98.69%, demonstrating its robustness in distinguishing between normal and anomalous data. Additionally, the model's performance across various metrics, including precision, recall, and F1-score, further solidifies its suitability for critical applications where real-time decision-making is paramount. The integration of feature selection and online learning ensures that the model is both scalable and computationally efficient, which is crucial for large-scale environments such as IoT and industrial systems. Future work could explore further optimizations for handling high-dimensional data and deploying the model in edge computing environments, where real-time processing is critical. Overall, this hybrid approach offers a promising solution for addressing the challenges of anomaly detection in dynamic, resource-constrained environments.

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