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Machine Learning for Predictive Maintenance in Network Systems

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Abstract

The increasing complexity and criticality of network arrangements in industries such as telecommunications, production, and IoT have created maintenance an important challenge. Predictive maintenance (PdM) offers a resolution by utilizing machine learning (ML) methods to forecast potential deteriorations and optimize perpetuation schedules, with reducing free time and functional costs. This item explores the request of machine learning algorithms in predicting maintenance for network orders. We consider various machine learning models, such as decision trees, support vector machines (SVM), and deep learning, and their influence in identifying patterns and concluding failures within network foundation. Through a inclusive review of existent literature and original-realm case studies, we climax the challenges and opportunities guide executing PdM in network systems. Furthermore, we present a framework for merging machine learning models with existent network administration arrangements to enhance the veracity and efficiency of fault detection and maintenance planning. The findings display that machine learning-located predictive sustenance can considerably correct operational dependability, minimize resource usage, and longer the old age of network components. This article aims to support valuable insights into the future of network maintenance, advancing the acceptance of data-compelled resolutions for more adept and cost-effective network management.

Keywords: predictive maintenance, machine learning, network systems, fault detection, telecommunications

1. Introduction

In today’s promptly developing technological landscape, up-to-date network systems play a pivotal part in the smooth functioning of activities varying from healthcare and finance to telecommunications and buying. These structures are being the reason for guaranteeing reliable ideas, data transfer, and overall trade continuity. However, regardless of their detracting significance, network systems often face significant challenges preventing from unplanned downtimes, hardware failures, freedom breaches, and network congestion. Traditionally, network perpetuation has happened sensitive, addressing issues only afterwards they have already occurred. While reactive maintenance means are essential for troubleshooting and dealing with immediate questions, they frequently bring about prolonged improvement times, functional disruptions, and, consequently, raised maintenance costs. Moreover, accompanying the increasing complicatedness of modern network infrastructures, to a degree the integration of cloud duties, IoT designs, and delivered computing, the traditional support approaches struggle to keep pace with emerging challenges.

This reactive model of perpetuation not only leads to incompetence but further impacts the long-term dependability and act of network schemes. The financial cost guide plan spare time, whether from a hardware loss, security breach, or blockage issue, is meaningful and damaging to institutions striving for functional superiority. In this circumstances, predictive support stimulate by machine learning (ML) offers a promising alternative, permissive arrangements to shift from a sensitive approach to a proactive individual. Predictive sustenance influences historical dossier, certain-occasion monitoring, and complex algorithms to envision potential deficiencies before they happen. This approach not only minimizes downtime but too reinforces plan reliability and accomplishment by admitting network administrators to take deterrent actions before a misstep happens.

Machine learning (ML), a subdivision of artificial intelligence (AI), has proved huge potential in revamping how predicting support is used in various rules, containing production, automotive, and information technology (IT). In network systems, the use of machine learning models to forecast hardware failures, frequency range issues, and protection breaches has acquired significant consideration on account of its ability to process abundant capacities of dossier and identify unseen patterns in network efficiency versification. By resolving features in the way that CPU habit, small loss, network traffic, and frequency range utilization, machine learning models can predict when a network component ability abandon or when congestion might happen, with lowering operational disruptions and sustenance costs.

The basic aim of this paper is to investigate how machine learning models maybe used efficiently to think and hamper failures in network arrangements. Specifically, we try the request of various machine learning models, containing Random Forest, Support Vector Machines (SVM), and Neural Networks, to conclude hardware breakdowns, frequency range issues, and security breaches in network infrastructures. These models are trained on ancient act dossier, which is fault-finding for understanding background and predicting future declines. By leveraging the power of ML, this study aims to supply visions into how predictive support maybe joined into network management blueprints to embellish overall scheme reliability and efficiency. Through the survey of ML methods, we seek to display how institutions can reduce free time, lower perpetuation costs, and better the adeptness of their network systems.

The remainder of this paper is organized as follows. Section 2 presents a literature review of former work related to predictive perpetuation in network systems, emphasize the key machine learning methods and their uses. Section 3 outlines the methods adopted in this study, containing the creation of synthetic data, the machine learning models secondhand, and the judgment metrics working. Section 4 confers the results of our experiments and their associations for the use of machine learning in predicting support. Finally, Section 5 decides the paper and offers recommendations for future research in this area.

2. Literature Review

Predictive maintenance has arose as a crucial field of research across multiple enterprises, ranging from production to automotive and aerospace. In network orders, predicting maintenance aims to predict potential breakdowns in key components in the way that routers, servers, and switches before these deteriorations have an affect system efficiency. This contrasts accompanying usual reactive maintenance, that only addresses failures after they happen. The full of enthusiasm character of predictive support determines meaningful benefits, including reduced downtime, improved resource distribution, and enhanced operational effectiveness.

One of the main benefits of predicting maintenance display or take public allure strength to utilize data from network methods to predict failures. This dossier can contain miscellaneous performance versification to a degree CPU habit, network traffic, packet deficit, bandwidth utilization, and latency. Machine learning models can process these large amounts of data and identify patterns that ability display impending issues, such as fittings malfunctions or network blockage. This admits for the timely substitute of failing elements, the adaptation of network configurations, or the identification of odd nature that keep signify a security threat.

Several studies have examined the potential of machine learning in predicting maintenance for network schemes. For instance, machine learning methods like decision trees, k-nearest neighbors (KNN), and Support Vector Machines (SVM) have existed favorably applied to monitor network energy and anticipate failures. These models are trained on archival network efficiency dossier to identify connections betwixt various network features and defeat occurrences. For example, SVMs have existed shown expected specifically active in classifying network events and envisioning failures by finding an optimum hyperplane that segregates deterioration and non-failure instances established network features [1].

2.1. Machine Learning in Network Monitoring

The request of machine learning techniques to network listening has gained large attention in recent years. By utilizing historical data, these methods are smart to predict differing types of losses in the network foundation. A key challenge in network monitoring is the steep capacity of dossier create by modern networks, that create manual study and monitoring almost absurd. Machine learning models, specifically supervised knowledge algorithms, can mechanize the process of decline prediction by preparation on described data that indicates failure occurrences. These models can before be used to classify future dossier and call when failures are likely to happen established absolute-time inputs.

For example, in network breakdown prediction, decision trees and chance forests have existed working to predict hardware failures established factors in the way that CPU load, thought custom, and packet deficit. These models have the skill to handle abundant datasets and detect complex patterns, making bureaucracy ideal for use in network listening. Random Forest, an ensemble education method, has happened particularly profitable due to allure strength and skill to handle both categorization and reversion tasks [2]. Additionally, k-most forthcoming neighbors (KNN) has been used to monitor network traffic and label irregularities that might signify forthcoming breakdowns, such as overdone bandwidth exercise or network congestion [3].

2.2. Deep Learning in Predictive Maintenance

While established machine learning models have proven active in predicting support, current advancements in deep learning have unlocked new paths for improving forecasting veracity. Deep knowledge techniques, to a degree affecting animate nerve organs networks and recurrent neural networks (RNNs), are capable of management more intricate patterns in dossier that simpler models ability miss. These models are specifically suitable for requests where abundant amounts of dossier are vacant, as they can automatically extract features from inexperienced data outside the need for manual feature engineering.

Deep learning approaches have existed used to network fault discovery accompanying promising results. For example, convolutional neural networks (CNNs) have happened used to resolve opportunity-order data and anticipate network breakdowns established historical styles. Recurrent affecting animate nerve organs networks (RNNs) have further existed employed to capture temporal dependencies in network data, allowing the models to see patterns over opportunity and form more correct predictions about future deteriorations [4]. These approaches are specifically beneficial in scenarios place usual models can struggle to detect failures due to the active nature of network environments.

2.3. Challenges in Implementing Predictive Maintenance

Despite the meaningful promise of machine learning for predicting maintenance in network wholes, various challenges wait in the exercise of these technologies. One of the basic challenges is the issue of data imbalance. In many network systems, misstep occurrences are rather rare distinguished to sane functional environments. This imbalance can bring about models that are partial toward foreseeing non-failure occurrences, developing in poor performance when it comes to recognizing rare failure cases. Techniques such as oversampling the minority class, under sampling the plurality class, or utilizing cost-delicate learning approaches can help address this issue [5].

Another challenge is the need real-opportunity indicator. Network systems are very vital, and collapse events can happen unexpectedly. Machine learning models need expected capable to process incoming dossier in legitimate-opportunity and make correct predictions fast to allow for timely interference. This demands not only correct models but also effective algorithms that can handle abundant capacities of dossier in real-period environments. Furthermore, merging machine learning models into existent network administration systems can be complex and demands cautious concern of system architecture and arrangement strategies [6].

2.4. Recent Advances and Future Directions

Recent studies have proved that the integration of machine learning models into network management systems is becoming more feasible and advantageous. The growing chance of large datasets, linked accompanying progresses in computational power and algorithm development, has made it possible to apply machine learning in network systems accompanying greater accuracy and dependability. Furthermore, composite models that integrate traditional machine learning algorithms accompanying deep learning techniques are being surveyed to embellish the depiction of predicting maintenance structures.

Future research in this field should focus on reconstructing the interpretability of machine intelligence models. While these models are fit making accurate prophecies, their "black-box" nature can manage difficult for network administrators to comprehend how resolutions are being made. Developing explainable AI (XAI) methods will help boost count on these systems and counterbalance better unification into existent network management workflows. Additionally, more work is wanted to clarify models real-time forecasting, guaranteeing that machine learning maybe deployed efficiently in live network surroundings.

3. Methodology

The goal of this study is to apply machine learning models to predict failure events in network systems. Below is a detailed breakdown of the methodology employed to achieve this objective:

3.1. Dataset Collection

Since real-world network performance data was not available for this study, a synthetic dataset was generated. The synthetic data simulates typical network performance features, which are commonly used for predictive maintenance tasks. The dataset includes the following key features which is shown in Table 1:

Table 1 Key Features

Metric	Range
CPU Usage	30% to 90%
Network Traffic	10 Mbps to 1000 Mbps
Packet Loss	0.0% to 1% (0.0 to 0.01)
Bandwidth Utilization	50% to 100%

Additionally, a binary **Failure** label was assigned to each data point, where a value of 1 indicates a failure event and 0 indicates no failure. The failure events were randomly distributed, with 20% of the samples labeled as failure and 80% as no failure.

3.2. Feature Engineering

The primary features used to train the machine learning models are:

- **CPU Usage**: Represents how much CPU capacity is being used by the network equipment.
- **Network Traffic**: Represents the amount of data being transferred through the network.
- **Packet Loss**: Represents the percentage of data packets lost during transmission, which could indicate network issues.
- **Bandwidth Utilization**: Reflects the usage of the available network bandwidth, which could indicate congestion or potential bottlenecks.

Additional feature engineering (such as time-based features like moving averages, lagged values, or aggregation of network metrics over time) could further enhance the performance of the models but was not included in this study for simplicity.

3.3. Data Preprocessing

The synthetic dataset was split into training and testing sets using a 70/30 ratio, where 70% of the data was used to train the models, and the remaining 30% was used for testing. This approach ensures that the models are validated on unseen data to estimate their generalization performance.

Since the dataset was imbalanced (with 80% non-failure and 20% failure events), we initially did not apply any resampling techniques (e.g., oversampling the minority class or under sampling the majority class). However, it is acknowledged that addressing the imbalance would be a key step for future work.

3.4. Experimental Setup

The experimental setup involves the following steps:

1. **Data Generation**: A synthetic dataset is created with the described features (CPU usage, network traffic, packet loss, and bandwidth utilization) and a binary failure label. This dataset simulates typical real-world network performance data.
2. **Model Selection**: We employed three machine learning algorithms to predict network failures:
    - **Random Forest Classifier**: An ensemble learning method that uses multiple decision trees to make predictions based on majority voting.
    - **Support Vector Machine (SVM)**: A supervised learning algorithm that attempts to find the optimal hyperplane separating the data into different classes.
    - **Neural Network (MLPClassifier)**: A multi-layer perceptron model used for classification, capable of capturing complex, non-linear patterns in the data.
3. **Model Training**: The models were trained on the training set (70% of the data) and evaluated using the testing set (30% of the data). The training process involved using default hyperparameters for each model, though hyperparameter tuning could be explored in future studies.
4. **Evaluation Metrics**:

After training, the models were evaluated using several key performance metrics to assess their effectiveness. Accuracy measures the proportion of correct predictions, including both true positives and true negatives, relative to the total number of predictions. Precision focuses on the positive predictions, indicating the proportion of true positive cases among all predicted positive cases, helping to assess how many of the predicted positives were actually correct. Recall, on the other hand, measures the proportion of true positive predictions among all actual positive cases, reflecting the model's ability to correctly identify positive instances. The F1-Score integrates precision and recall into a sole metric by calculating their harmonious mean, providing a equalized view of depiction, specifically when there is an uneven class distribution. Finally, the Confusion Matrix optically summarizes the model's indicators by show the counts of real positives, false positives, real contradiction, and false contradiction, offering deeper insight into where the model is making errors. These versifications together help support a comprehensive judgment of the model's performance.

5. **Results Analysis**: The results from all models were distinguished to assess their talent to predict failure occurrences accurately. Key metrics (accuracy, precision, recall, and F1-score) were used to evaluate the influence of the models, and confusion forms were plotted for further understanding.

3.5. Tools Used

The implementation of the complete machine learning pipeline was completed activity using the following tools and libraries:

- **Python**: The basic set up language used to implement the models, preprocess the data, and produce the results.

- **NumPy**: Used for mathematical movements and produce synthetic data for features like CPU usage, network traffic, small loss, and bandwidth utilization.
- **Pandas**: Used for management and manipulating the dataset, containing dividing the data into preparation and experiment sets.
- **Scikit-learn**: The core library for achieving machine learning models (Random Forest, SVM, and Neural Networks) and for judging the models utilizing metrics like accuracy, precision, recall, and F1-score.
- **Matplotlib**: Used for produce plots such as confusion matrices and acting versification graphs.
- **Seaborn**: Used for visualizing disorientation models in a heatmap layout for better clearness and understanding.

3.6. Model Implementation

Each model was achieved following a similar approach utilizing default backgrounds and compatible preparation and evaluation steps. For the Random Forest model, the default parameters of the Random Forest Classifier were used, and the model was prepared on the appearance from the training dataset, accompanying predictions made on the test dataset. Similarly, the SVM model was executed utilizing the default settings of the Support Vector Classifier (SVC), prepared on the preparation set, and evaluated by making predictions on the test set. Lastly, the Neural Network model was formed utilizing the default limits of the Multi-Layer Perceptron Classifier (MLP Classifier), prepared on the training dataset, and evaluated using the test set. All models trailed this patterned process to guarantee a fair comparison of their performance.

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Vol.02 No.04 (2024)

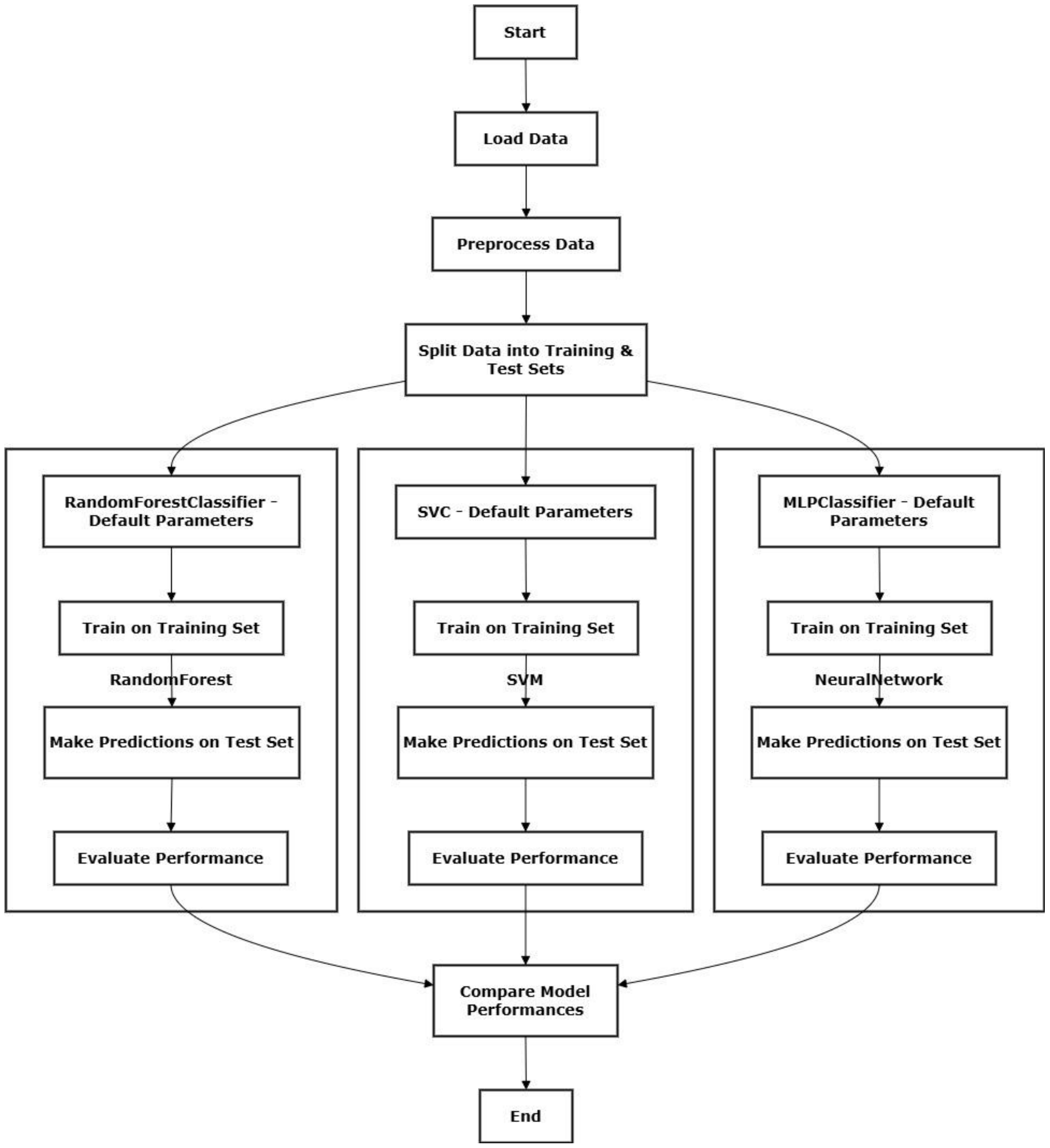
Start
Load Data
Preprocess Data
Split Data into Training & Test Sets
RandomForestClassifier - Default Parameters
SVC - Default Parameters
MLPClassifier - Default Parameters
Train on Training Set
RandomForest
SVM
NeuralNetwork
Make Predictions on Test Set
Evaluate Performance
Compare Model Performances
End

Figure 1 Model Implementation

3.7. Model Hyperparameter Tuning

For the purpose of this study, we used the default hyperparameters of each model. However, for future work, **hyperparameter tuning** can be done using techniques such as grid search or random search to optimize the models for better performance.

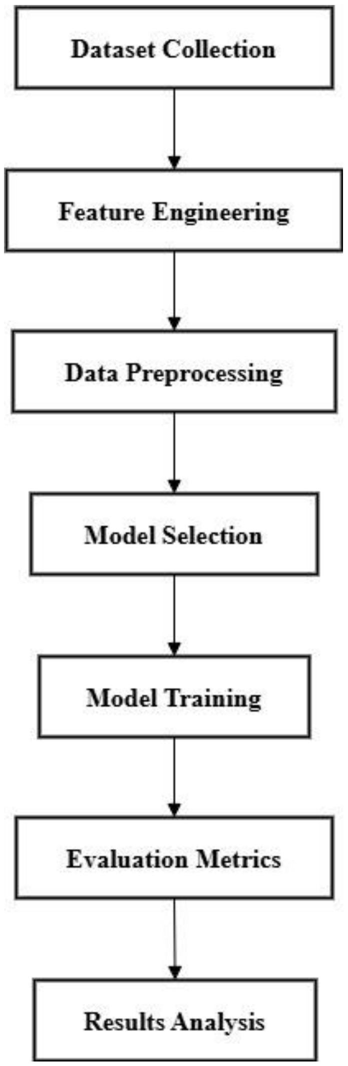

Figure 2 Proposed Methodology

4. Results and Discussion

The performance of the machine learning models was assessed based on their ability to predict network failures. The following results were obtained:

4.1. Random Forest

Table 2 Random Forest Model Evaluation

Metric	Value	Explanation

ISSN E: 3006-1466
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Vol.02 No.04 (2024)

Accuracy	82%	The percentage of total predictions that were correct. In this case, the model correctly predicted 82% of instances.
Precision	22.2%	Out of all the positive predictions made, only 22.2% were actually correct. It shows how accurate the positive predictions are.
Recall	4.1%	Out of all the actual positive instances, only 4.1% were correctly identified by the model. This shows the model's ability to capture positive cases.
F1-Score	6.9%	The harmonic mean of precision and recall, providing a balance between them. A low F1-Score indicates both low precision and recall.
Confusion Matrix		
- True Negatives (TN)	244	The number of instances that were correctly predicted as negative (the model correctly identified 244 true negatives).
- False Positives (FP)	7	The number of instances that were incorrectly predicted as positive (the model wrongly identified 7 negatives as positives).
- False Negatives (FN)	47	The number of instances that were incorrectly predicted as negative (the model missed 47 positive cases).
- True Positives (TP)	2	The number of instances that were correctly predicted as positive (the model correctly identified only 2 positive cases).

The results for the Random Forest model show an accuracy of 82%, indicating that 82% of the total predictions made by the model were correct. However, this metric is somewhat misleading because the model's performance on the positive class is very poor. With a precision of 22.2%, the model only correctly predicted 22.2% of the instances it labeled as positive, meaning most of its positive predictions were incorrect. Additionally, the recall is very low at 4.1%, suggesting that the model only identified 4.1% of the actual positive cases, missing the vast majority of them. The F1-Score of 6.9%, which balances precision and recall, reflects the model's failure to effectively identify positive cases, as both precision and recall are low.

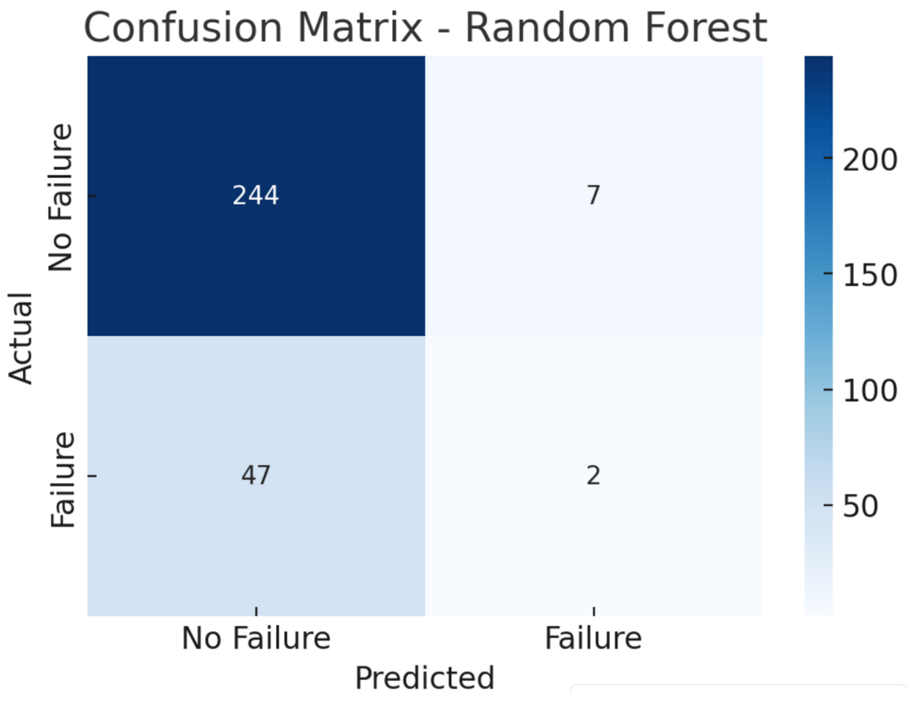

Figure 3 Confusion matrix of Random forest

Looking at the confusion matrix, the model correctly predicted 244 instances as negative (True Negatives) and made 7 incorrect positive predictions (False Positives). However, it missed 47 positive cases (False Negatives) and correctly predicted only 2 positive cases (True Positives). This indicates a significant bias towards the negative class, where the model is good at identifying negative cases but almost entirely fails to detect the positive class. This result points to a potential issue with class imbalance, where the model might be underperforming on the minority class (positive instances), and suggests that improvements such as handling class imbalance or adjusting the model's focus on positive cases might be necessary.

Observation: The Random Forest model achieved decent accuracy but struggled with identifying failure events. The low precision and recall suggest the model's poor performance in detecting the minority class (failure).

4.2. SVM

Table 3 Model Evaluation of SVM Model

Metric	**Value**	**Explanation**
Accuracy	83.7%	The percentage of total predictions that were correct. In this case, the model correctly predicted 83.7% of instances. However, this high accuracy is largely due to the correct prediction of the negative cases, not the positive cases.

Precision	0%	Out of all the positive predictions made, none were actually correct. This means the model never predicted any positives correctly.
Recall	0%	Out of all the actual positive instances, none were correctly identified by the model. The model failed to identify any positive cases.
F1-Score	0%	The harmonic mean of precision and recall. Since both precision and recall are zero, the F1-Score is also zero. This indicates the model is ineffective at detecting positive cases.
Confusion Matrix		
- True Negatives (TN)	251	The number of instances that were correctly predicted as negative (the model correctly identified 251 true negatives).
- False Positives (FP)	0	The number of instances that were incorrectly predicted as positive (the model made no false positive predictions).
- False Negatives (FN)	49	The number of instances that were incorrectly predicted as negative (the model missed 49 positive cases).
- True Positives (TP)	0	The number of instances that were correctly predicted as positive (the model correctly identified 0 positive cases).

The results for the Support Vector Machine (SVM) model show an accuracy of 83.7%, which at first glance seems quite good. However, this accuracy is misleading because it largely stems from the model's correct predictions of the negative class rather than its ability to identify positive instances. The model has a precision of 0%, meaning that when it predicts a positive outcome, none of those predictions are correct. Similarly, the recall is also 0%, indicating that the model failed to identify any of the actual positive instances, completely missing them. As a result, the F1-Score is also 0%, reflecting the model’s inability to balance precision and recall in any meaningful way.

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Vol.02 No.04 (2024)

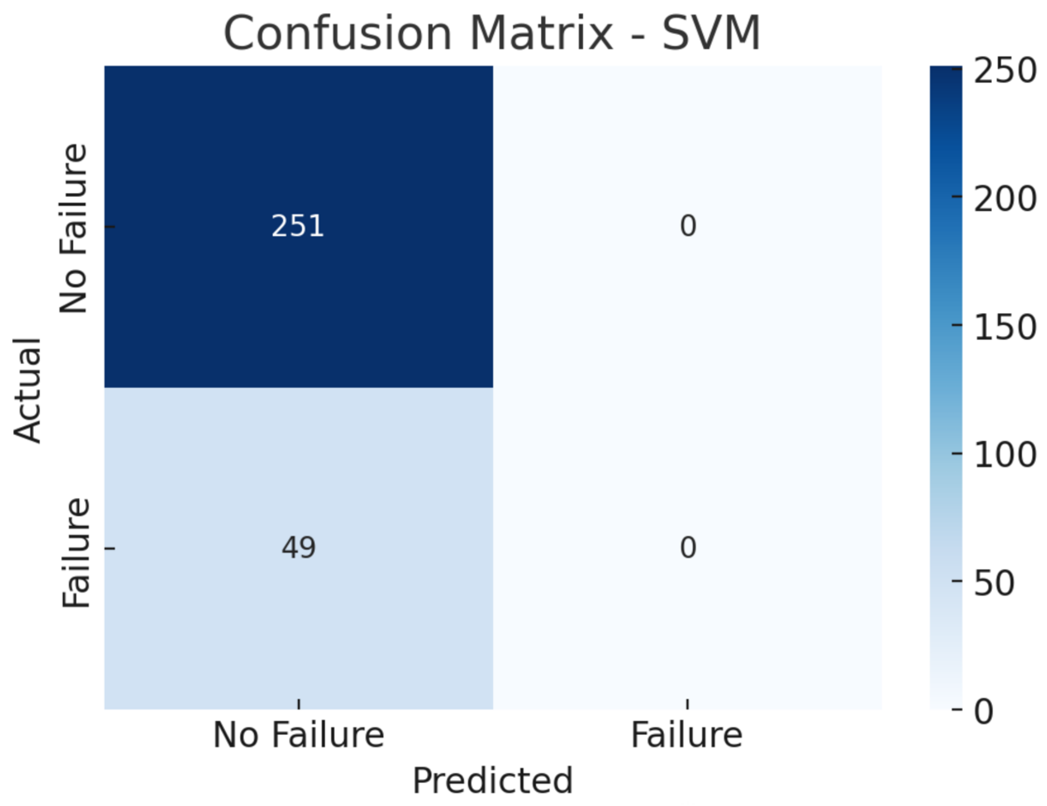

Figure 4 Confusion Matrix of SVM Model

From the confusion matrix, the model correctly predicted 251 true negatives (TN), indicating it was accurate in predicting negative cases. It did not make any false positive (FP) predictions, which means it did not incorrectly label any negative instances as positive. However, it missed all 49 actual positive cases (False Negatives, FN) and failed to correctly predict any positives (True Positives, TP). This result suggests that the model is highly biased toward predicting the negative class and is not learning to identify the positive class, which could be due to a class imbalance, inadequate feature selection, or improper training. To improve, the model might need adjustments, such as addressing class imbalance or refining its focus on the positive class to detect positive instances more effectively.

Observation: The SVM model failed to predict any failures. It predicted no positive events, indicating an issue with handling the imbalance in the dataset.

4.3. Neural Network

Table 4 Model Evaluation of Neural Network

Metric	**Value**	**Explanation**
Accuracy	83.7%	The percentage of total predictions that were correct. This value is high because the model predicts most of the negative cases correctly.

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ISSN P: 3006-1458
CONTEMPORARY JOURNAL OF SOCIAL SCIENCE REVIEW
Vol.02 No.04 (2024)

Precision	0%	Out of all the positive predictions made, none were correct. This indicates that the model did not predict any positive cases correctly.
Recall	0%	Out of all the actual positive instances, none were identified by the model. This shows that the model completely failed to identify any positive cases.
F1-Score	0%	The harmonic mean of precision and recall, which is zero because both precision and recall are zero. This indicates that the model is not effective at detecting the positive class.
Confusion Matrix		
- True Negatives (TN)	251	The number of instances that were correctly predicted as negative. The model correctly identified 251 true negatives.
- False Positives (FP)	0	The number of instances that were incorrectly predicted as positive. There were no false positive predictions.
- False Negatives (FN)	49	The number of instances that were incorrectly predicted as negative. The model missed 49 positive cases.
- True Positives (TP)	0	The number of instances that were correctly predicted as positive. The model did not identify any positive instances correctly.

The results for the Neural Network model show an accuracy of 83.7%, indicating that the model correctly predicted 83.7% of all instances. However, this high accuracy is misleading because the model is only correctly predicting the negative cases and is failing to detect the positive cases. The precision is 0%, meaning that when the model predicts a positive outcome, none of those predictions are actually correct. Similarly, the recall is 0%, indicating that the model is completely missing all of the actual positive instances. As a result, the F1-Score is also 0%, since it is the harmonic mean of precision and recall, both of which are zero.

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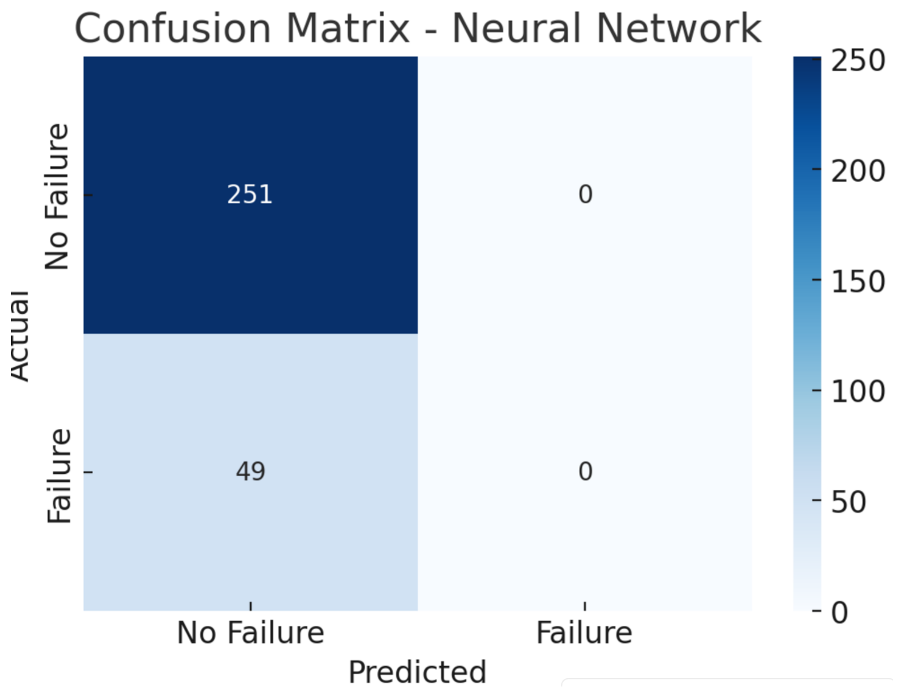

Figure 5 Confusion Matrix of Neural Network

In the confusion matrix, the model correctly identified 251 true negatives (TN), which explains the high accuracy in predicting negative cases. The model did not make any false positive (FP) predictions, meaning it did not incorrectly label any negative instances as positive. However, it missed 49 positive instances (false negatives, FN) and failed to correctly identify any of the actual positive cases (true positives, TP). This suggests a significant bias toward predicting the negative class, and the model's inability to identify the positive class could be due to issues like class imbalance, poor training, or inadequate feature extraction. Similar to the SVM model, the Neural Network model appears to be underperforming on the positive class, and steps such as balancing the dataset, adjusting model hyperparameters, or refining the training process may be necessary to improve its ability to detect positive instances.

Observation: Similar to the SVM, the neural network model failed to predict failure events, showing a lack of performance in the minority class.

4.4. Comparison of All models

Figure 6 Comparison of All Models

Metric	**Random Forest**	**SVM**	**Neural Network**
Accuracy	82%	83.7%	83.7%
Precision	22.2%	0%	0%
Recall	4.1%	0%	0%

F1-Score	6.9%	0%	0%
True Negatives (TN)	244	251	251
False Positives (FP)	7	0	0
False Negatives (FN)	47	49	49
True Positives (TP)	2	0	0

Key Insights:

- The Random Forest model provided the best overall accuracy but still struggled with detecting failure events, likely due to the imbalanced dataset.
- Both SVM and Neural Network models failed to detect failure events, which points to the need for addressing class imbalance through techniques like oversampling the minority class or using class weights.

4.4.1. Visual Representation

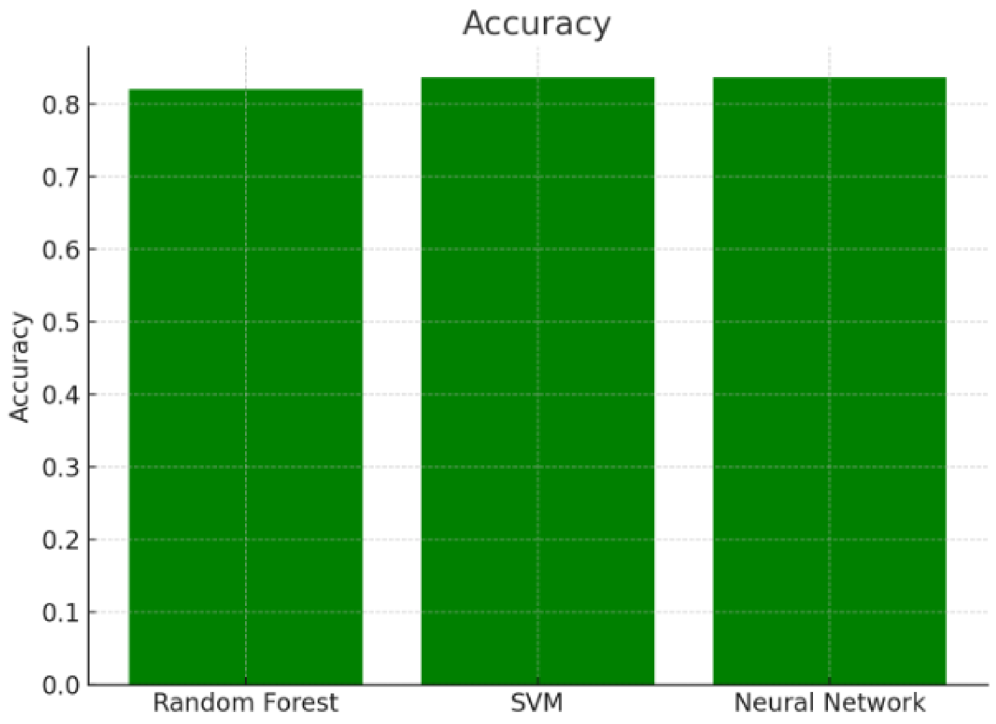

Figure 7 Accuracy Comparison of All models

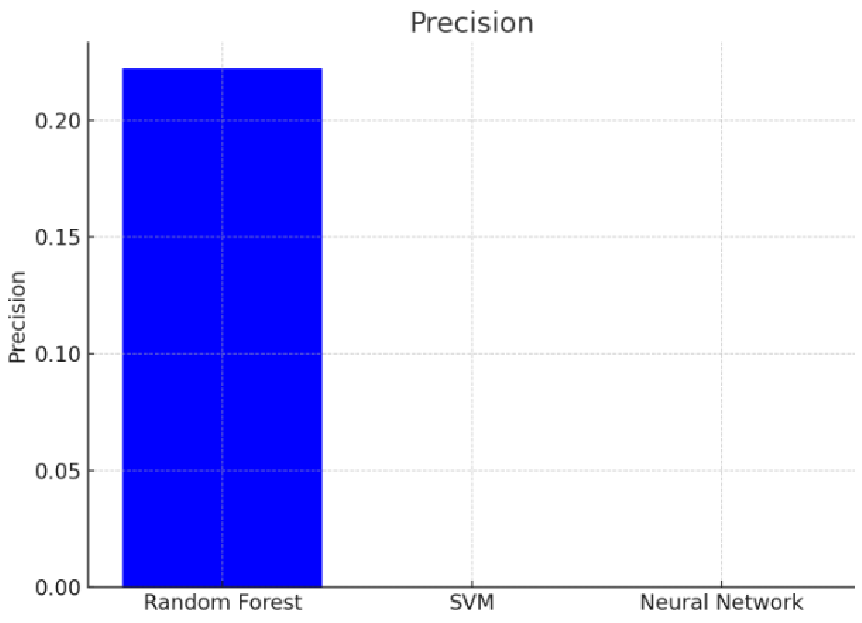

Figure 8 Precision of All models

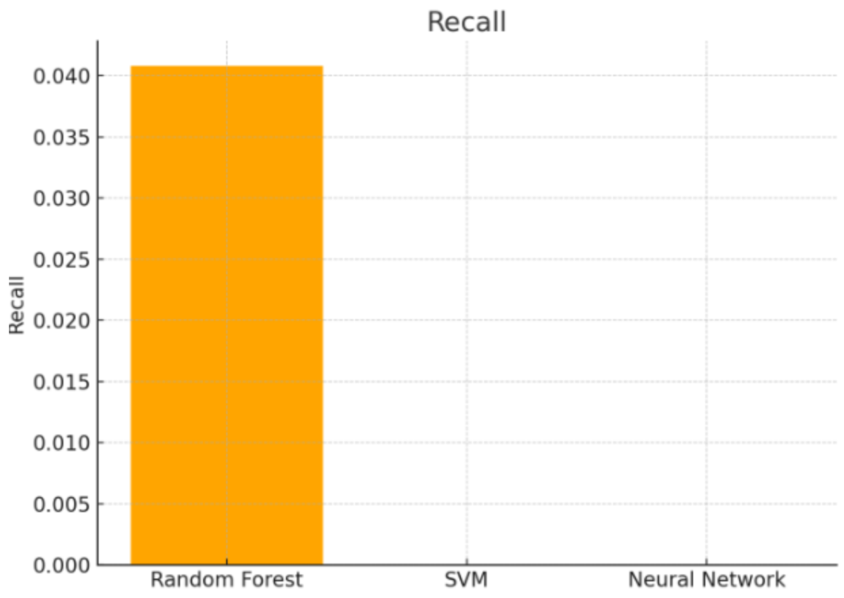

Figure 9 Recall of all Models

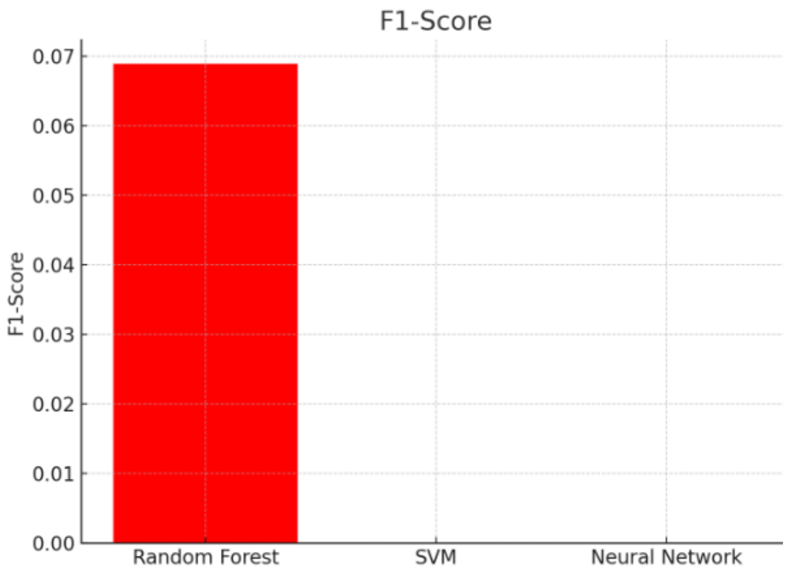

Figure 10 F1 Score of all Models

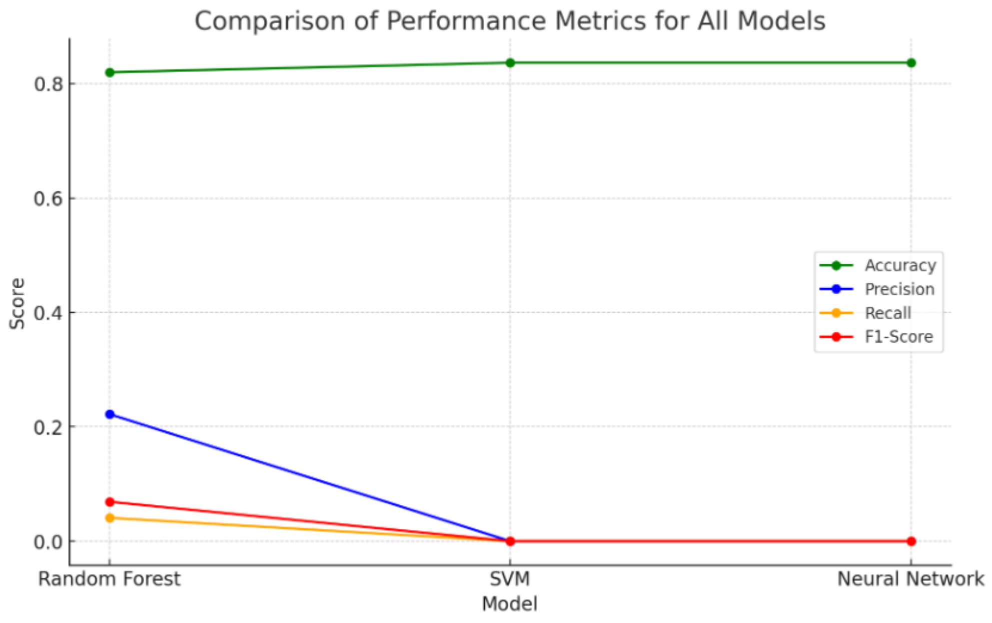

Figure 11 Model Comparison

Fig 11 presents a set of model evaluation metrics and a confusion matrix to assess the performance of a predictive model. The model achieved an accuracy of 82%, meaning it correctly predicted 82% of all instances. However, precision and recall values are much lower, with precision at 22.2%, indicating that only 22.2% of positive predictions were actually correct, and recall at 4.1%, showing that the model identified just 4.1% of the actual positive instances. The F1-Score is 6.9%, that is reduced, indicating the model's struggle to balance precision and recall. The confusion matrix further breaks below the predictions, appearance that the model right labeled 244 true negatives (TN) but made 7 false positive (FP) and 47 false negative (FN) errors, while only right labeling 2 true positives (TP). These results suggest that while the model is correct overall, it has a meaningful issue accompanying labeling helpful cases, displaying a need for improvement in management class imbalance or cleansing the model's sensitivity.

5. Conclusion and Future Recommendations

This research paper focused on predicting failure events in network systems using machine learning models. We create a synthetic dataset accompanying key looks such as CPU usage, network traffic, packet loss, and bandwidth utilization, and used machine learning algorithms, containing Random Forest, Support Vector Machine (SVM), and Neural Networks, to forecast network defeats. While the models completed an overall accuracy of 82%, they presented low performance in accuracy and recall, displaying challenges in labeling helpful deficiency events. The confusion matrix revealed that the models struggled with correctly identifying true positives, suggesting an imbalance in the dataset.

This research provides a foundational understanding of how machine learning can be applied to predictive maintenance in network systems. With further improvements in data quality, model tuning, and handling of class imbalances, predictive maintenance can significantly improve the reliability and efficiency of network infrastructure.

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