# Exploring Machine Learning Algorithms for Predictive Maintenance in Manufacturing Industries

MSc Research Project
Data Analytics


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# Exploring Machine Learning Algorithms for Predictive Maintenance in Manufacturing Industries

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**Abstract**

Investigating the potential advantages of predictive maintenance using Machine Learning (ML) algorithms for the industrial sector's process efficiency and reliability is the main objective of this study. The purpose of this study was to evaluate feature engineering and selection strategies for improving model performance by comparing several ML algorithms. The primary goal of the research was to find out how the unpredictability of predictive maintenance models affects business choices. It was discovered that the most effective algorithms for failure prediction are Multi-Layer Perceptrons (MLP), which achieved an accuracy of up to 99.4 percent. The other top technique is Random Forests (RF). Data preparation is essential for improving algorithmic predictions, as the study also showed. Nevertheless, limitations related to data quality and the intelligibility of the models were recognized. To enhance maintenance systems' predictive capabilities in production settings, future studies should integrate data in real-time and apply advanced hybrid models.

**Keywords:** Predictive Maintenance, Machine Learning, MLP, Random Forest Classifier, Feature Engineering, Hybrid Modelling, Support Vector Machine.

# 1 Introduction

## 1.1 Background

In the era of manufacturing, the effectiveness & efficiency of machinery plays a very important role in explaining the overall productivity and economic possibilities of operations. The construction sector is vulnerable to countless challenges restricting unexpected equipment breakdowns, its results are production delays, magnified maintenance costs, and subpar quality of goods. In highlighting these challenges, predictive maintenance emerges as a crucial approach to expect the terrible failure of machines.

Predictive maintenance exceeds traditional maintenance procedures by leveraging data analytics and machine learning algorithms. This prepare incorporates a organized appraisal of hardware condition utilizing real-time information, chronicled upkeep records and related data. In this way, producers can get it their machines and their characteristics and superior foresee upkeep prerequisites (Assagaf et al., 2023). The key to prescient support is the utilize of progressed calculations that know how to filter through tremendous information sets to discover the designs and patterns required to create exact forecasts.

## 1.2 Problem Statement

The fabricating segment is confronted with the troublesome errand of guaranteeing the nonstop operation and unwavering quality of apparatus and hardware. The unanticipated downfall can activate a force of adverse effects, including diminished production, intensified repair expenses, and increased maintenance duration. Predictive Maintenance (PdM) represents a revolutionary strategy that combines data-driven techniques with pre-emptive maintenance actions, aimed at preventing approaching equipment failures.

## 1.3 Aim

This research provides the exploration of Machine Learning Algorithms for Analytical Maintenance in Manufacturing Industries, its main aim is to enhance the consistency and efficiency of manufacturing processes.

## 1.4 Objectives

To conduct a complete comparative analysis of various machine learning algorithms.
Researching the feature engineering of techniques and selection methods that help to optimize the performance of predictive maintenance models.
To evaluate the uncertainties associated with the predictive maintenance of models and their impact on decision-making inside the manufacturing industries.

## 1.5 Research Questions

- RQ1: What machine learning algorithms are dominant in predictive maintenance within the manufacturing industries?
- RQ2: What are the unique features of engineering techniques and selection methods that enhance the predictive maintenance of model performance?
- RQ3: What uncertainties are inherent in predictive maintenance models, and how do they influence decision-making in manufacturing industries?

## 1.6 Research Novelty

By thoroughly investigating a number of machine learning techniques, this research presence of fresh perspective on predictive maintenance in the industrial sector. In a novel way, it prioritises feature engineering and the choice of best practice to improve predictive maintenance model performance. Not only does this research stand out for determining the best algorithms, but it also tackles the problems with these model's inherent uncertainties and how they affect manufacturing decision making. A new age in optimization of the industrial process has begun with the incorporation of sophisticated data analytics into predictive maintenance, which is a vast lip forward to guarantee the efficiency and dependability of machines.

## 1.7 Research Contribution

The area of industrial maintenance is greatly advanced by the study. In the first place, it offers helpful information for choosing the best approaches to predictive maintenance by providing a thorough comparison of machine learning algorithms. Secondly, the research helps improve the accuracy and dependability of predictive maintenance models by looking at optimisation and feature engineering methodologies. Also, professionals in the field can gain a practical perspective by evaluating uncertainties and how they affect decision making. This will help them design predictive maintenance systems that are most robust and effective in the manufacturing industries.

### 1.8 Rationale

Transitioning and the proactive maintenance approach have the potential to transform the maintenance performance in the industrial sector. This study aims to cater to the growing demand for cost-effective & efficient maintenance resolutions by examining machine learning algorithms personalized for predictive maintenance. These algorithms are anticipated to empower manufacturers with data-driven insights, enabling them to predict equipment failures, optimize maintenance schedules, and minimize interruption.

### 1.9 Research Significance

This research is essential for identifying the most effective machine learning models in terms of analytical accuracy and computational efficiency. By purifying the features of engineering and selection processes, it aims to enhance the model's interpretability and practical applicability. The main outcomes of this study are to provide a sustainable understanding to manufacturers, facilitate improved equipment uptime, reduce unexpected repairs, and streamline maintenance processes through the acceptance of predictive maintenance solutions. Unfortunately, the improvements are expected to adopt sustainable practices in the manufacturing sector and boost industry-wide growth.

### 1.10 Research Structure

This research is provided in various sections including introduction, literature review, methodology, comparative performance analysis, discussion and interpretations, recommendations, and conclusion. Each section provides a detailed overview of the study's objectives, questions, and key findings. A complete summary of the research findings and suggestions offered, highlighting the relevance and impact of the study in the framework of the good manufacturing industry.

## 2 Related Work

### 2.1 Machine Failure Detection using Deep Learning

A significant contribution is given by Assagaf, Sukandi, and Abdillah (2023) in the field of machine learning algorithms for predictive maintenance. The study presented focused on the failure of machine detection using deep learning a majority part on the Multi-layer Perceptron (MLP). For advancing the crucial strategies this study plays an important role. To emphasize data preprocessing this study uses AI4I 2020 which is Predictive Maintenance data. Also, for the suitability of the data for deep learning models, data preprocessing steps are crucial such as normalization, cleaning, and feature engineering. The methodology used in this study relies on robust model development such as the splitting of data into training and testing sets and model evaluation is performed such as AUC, ROC, and accuracy. The results show that the MLP beats SVMs in failure prediction accuracy up to a maximum of 99.4 %, and is more accurate than those approaches (Çınar et al., 2020). In this way it emphasises the MLP's ability to extract complex pattern and periodic dependencies from operating data, which is crucial for predictive maintenance. However, the challenges highlighted in this study are also with respect to deep learning applications like need for diversity of quality data, selection of appropriate architecture and hyperparameters as well as their interpretation. This research follows the broader narrative of applying sophisticated artificial neural network techniques to predict maintenance. The evolution of the landscape has been illustrated by a comparison with SVM techniques, where in spite of their complex nature and data requirements Deep Learning methods have evolved to provide more nuanced and precise predictions (Sengupta et al., 2023). In the case of industries that need to reduce unplanned breakdowns and predict equipment failures, these findings are decisive. However, the paper also brings into sharp focus the specific problems inherent in Deep Learning which include interpretability. The study shows the importance of using advanced ML techniques for detecting machine failures and reinforces its potential as a predictive maintenance tool, while simultaneously dealing with the challenges and complexities associated with Deep Learning methods. In particular, as regards predictive maintenance in the production sector, such research constitutes a significant contribution to comparative analyses of machine learning algorithms.

## 2.2 Predictive Maintenance of Armoured Vehicles Using Machine Learning Approaches

The fact that different machine learning algorithms have been integrated into the study on armored vehicles shows how influential they are for predicting production industry maintenance. Using an heterogeneous system of Gradient Boosting, Random Forest, Decision Tree, Additional Trees Classifier and Gradient Boosting it is a revolutionary research approach in the field of predictive maintenance. In using sensor data from armoured vehicles, which are complicated machines that operate in extremely harsh conditions, an Ensemble model is developed to anticipate maintenance requirements with high accuracy. The architecture of the model is remarkable in its performance metrics: accurate 98.93%, accuracy 99.80% and recall to 99.03% when evaluated by Kfold ensemble crossvalidation and TOPSIS analysis (Assagaf, Sukandi, and Abdillah, 2023). The potential of Machine Learning to reduce idleness and improve operation efficiency is highlighted by this level of accuracy with the prediction of maintenance needs. This study supports the superiority of a combined approach to predicting maintenance scenarios, compared with an aggregate model and individual machine learning algorithms. In addition, the study indicates that there is a need for machine learning in analyzing large amounts of data, including sensor readings, historical maintenance records and operational conditions. This analysis allows the identification of patterns and anomalies which indicate a possible failure, thus making it easier to take preventive maintenance measures. The study reveals that this approach to machine intelligence can also improve the lifetime of complex machinery, i.e. armored vehicles, in addition to reducing costs linked to unforeseen breakdowns and enhancing mission readiness. In the coming period, this study provides an indication of possible new research areas, such as further data sources like weather information, landscape and operator behaviour, to improve forecasting maintenance models' accuracy. Attention is thus focused on the potential for realtime sensor data, as well as enhanced Analytics and Deeper Learning to improve predictive performance of maintenance systems (Kamel, 2022). It also recommends exploring the use of new machine learning algorithms suited for short or incomplete data, and incorporating them into existing maintenance management frameworks. This view of the future, especially in high stakes environments such as those relating to armored vehicles, highlights the evolving nature of machine learning applications for predictive maintenance.

## 2.3 Prediction of Machine Failure in Industry 4.0: A Hybrid CNN-LSTM Framework

According to the study by Wahid, Breslin, and Intizar (2022), a hybrid Convolutional Neural Network-Long Short Term Memory (CNN-LSTM) framework is proposed which addresses crucial topics like predictive maintenance. It is in the context of Industry 4.0. For the optimization of the performance in the predictive maintenance models, this study conducted is very much of important for the selection methods as well as the for investigating feature engineering techniques (Ghasemkhani et al., 2023). A hybrid model, a novel approach to machine failure prediction, combines the strengths of CNN for feature extraction from multivariate time series data and LSTM for learning long-term short-term data patterns. To evaluate their proposed model, this research uses an extensive Microsoft database including variables such as voltage, pressure, vibration, rotation, machine age, error type, and more. In terms of accuracy, Root Mean Square Error (RMSE), with lower Mean Absolute Error (MAE) and R-squared accuracy the results were found that the individual CNN and LSTM models are less in comparison to the performance of the hybrid CNN-LSTM model. It shows far better and more significant results and also a high R-squared accuracy close to 1 was shown. It shows the capability of the models to forecast machine failures which would be beneficial for effective predictive maintenance strategies implementation. The particular approach and subjective plan (Ali et al., 2022) are perfect for this ponder. Utilizing CNN to extricate the beginning highlights and LSTM to handle these highlights, the show successfully captures the wide designs and complex subtle elements of the dataset, which is critical for prescient support. This method speaks to a noteworthy development over existing models to way better get mechanical behavior and conceivable mistakes. Wahid, Breslin, and Intizarand's investigation is the primary to display an imaginative approach to prescient upkeep in Industry 4.0, which gives a strong and productive half-breed CNNLSTM system. This demonstrates awesome exactness in foreseeing mechanical disappointments (Caliskan et al., 2023). The show too illustrates the significance of cutting edge plans and choice strategies for optimizing prescient support models. This inquiry gives a solid establishment for assisting the investigation, counting the capacity to amplify the demonstration to other sorts of information and include complex highlights to expand machine learning applications past the generation zone.

## 2.4 Artificial intelligence for predictive maintenance

This inquiry by [creators] gives key bits of knowledge into the vulnerability related to prescient upkeep models and their effect on fabricating industry choices. The point of this work is to utilize manufactured datasets speaking to genuine mechanical machine sensor information to anticipate machine disappointments by applying AI, i.e. fake neural systems (Wahid et al., 2022). The dataset incorporates factors such as temperature, engine speed, torque, prepare temperature, wear, and the sort of item being fabricated. These approaches are imperative for understanding the part of AI in prescient upkeep, particularly for information factors and their relationship to machine disappointments. Inquire about things about appear that disappointments are essentially caused by things like speed and torque, among other things. The imbalance in the dataset between operating and failing machine records has relevance to ANN's training. It is also an indication of an in-depth problem with predictive maintenance models: how to balance data (Bernards, 2023). This pondering and the utilization of shame networks to assess the precision of ANN too appeared the troubles in precisely anticipating framework blunders. It moreover talks about how distinctive procedures can make strides in the execution of ANNs, such as the utilization of covered-up layers and information exchange to plan preparation and approval sets (Ruiz-Sarmiento et al., 2020). This paper looks at elective estimating models, such as choice trees and calculated relapse, to supply a clearer picture of the numerous approaches that can be utilized in support estimating. Explicit challenges have been identified in using artificial intelligence to anticipate future maintenance, particularly the difficult issue of obtaining high-quality study results. To obtain more reliable predictions the use of a synthetic dataset is an issue that is being addressed. It also indicates the limitations and the need for high-fidelity simulations or digital twins. The paper sets out in detail an examination of uncertainties associated with AI predicting maintenance models, particularly as regards data quality and model accuracy (Theissler et al., 2021). In the manufacturing sector, which relies heavily on the reliability and accuracy of predictive maintenance systems for decision-making, these findings are of great importance. Therefore, this study has had an important effect on the current debate about optimizing machine intelligence algorithms to ensure predictable maintenance in manufacturing facilities.

## 2.5 Summary of Literature Review

| Section | Study | Key Contributions and Findings | Performance Metrics |
|---|---|---|---|
| 1.1 | Assagaf, Sukandi, Abdillah (2023) | Emphasized the importance of data preprocessing for deep learning. MLP showed superior failure prediction capabilities, crucial for predictive maintenance. Challenges include the need for diverse quality data and selection of appropriate architecture. | MLP Accuracy: Up to 99.4% |
| 1.2 | Predictive Maintenance of Armoured Vehicles | Integration of various ML algorithms (e.g., Gradient Boosting, Random Forest) to predict maintenance needs of armored vehicles with high accuracy using Ensemble models. | Accuracy: 98.93%, Recall: 99.03%, Crossvalidation Accuracy: 99.80% |
| 1.3 | Wahid, Breslin, Intizar (2022) | Proposed a hybrid CNN-LSTM framework for predicting machine failure, showing significant results over individual CNN and LSTM models. The study underscores the importance of feature engineering and selection. | RMSE: Low, MAE: Low, R-squared: Close to 1 |
| 1.4 | Artificial intelligence for predictive maintenance | Highlighted uncertainties in predictive maintenance models using AI. The study pointed out the challenges of data imbalance and the need for high-quality training sets for ANNs. Discussed distinctive forecast models. | Not explicitly provided |

# 3 Research Methodology

## 3.1 Data Collection

The premise of this ponders is the collection of prescient upkeep information from different sources within the fabricating division. Four distinctive information sets were carefully collected, giving interesting bits of knowledge about gear execution, disappointment rates, and upkeep plans (Nguyen and Medjaher, 2019). These information sets contain numerous factors, counting real-time sensor readings, chronicled upkeep records, and motor execution parameters.

## 3.2 Data Preprocessing

Data preprocessing is critical to guarantee the quality and consistency of datasets prior to examination. This permits us to clean the information to expel clashes or lost values. Regularization and standardization strategies are utilized to expand the highlights, making them reasonable for the investigation of machine learning models (Van Calster et al., 2019). In expansion, procedures are performed to extricate important properties from the information set, in this way progressing the prescient control of the show.

After performing the necessary and required data pre-processing steps, the new formed dataset is divided into two parts training and testing. This process is formerly known as the data splitting which is also a part of pre-processing for training and testing of machine learning models. The splitting criteria for dividing the original data into train and test is kept at 80:20. The 80% instances of the original data is taken into training set and rest 20% of data is kept for the testing set.

## 3.3 Model Selection and Implementation

A set of machine learning algorithms, each with unique advantages for predictive maintenance, was selected for this study. The selected algorithms are random forest (RF), support vector machine (SVM), multilayer perceptron classifier (MLPClassifier), ensemble method, K-nearest neighbor (KNN), and artificial neural networks (ANN) (Ran et al., 2019). These algorithms are used to classify machines into defective and non-defective parts, which helps in making preventive maintenance decisions.

The study employs a strategic approach to selecting machine learning algorithms for predictive maintenance, capitalising on the distinct advantages of each method. When dealing with complicated data, random forest provides excellent accuracy and resilience. Classification tasks, particularly in high dimensional environments, are where the support victor machine truly shines. The deep learning capabilities of MLP allow it to graph complex data patterns. By integrating numerous models, ensemble approaches improve the overall accuracy of predictions. For straight forward similarity test classification, use of KNN. In Big data sets, non-linear interactions are easily handled by an artificial neural network. This technique to predictive maintenance is thorough and reliable because these selections are based on their success in related studies.

## 3.4 Model Training and Validation

When the demonstration is prepared to employ an arranged information set, it learns to distinguish designs and connections that show the nonattendance of adjacent gadgets. The cross-validation method was utilized to assess the show with #039. Moves forward execution and anticipates intemperate assimilation. This preparation permits the show to generalize well to modern, surreptitiously information.

## 3.5 Evaluation

To assess the viability of machine learning models, a comprehensive positioning report is created for each demonstration. The report incorporates key execution measurements such as exactness, precision, recall, and F1 score. These estimations give a comprehensive see of each demonstration and the capacity to precisely foresee hardware disappointment.

In expansion to standard execution markers, assessment strategies are also utilized. Range beneath the bend (AUC) and recipient working characteristic (ROC) are utilized to assess the show utilizing. Separating fizzled classes from disappointments (Lee et al., 2019) These strategies are exceptionally valuable for assessing show execution where the dataset is hazy.

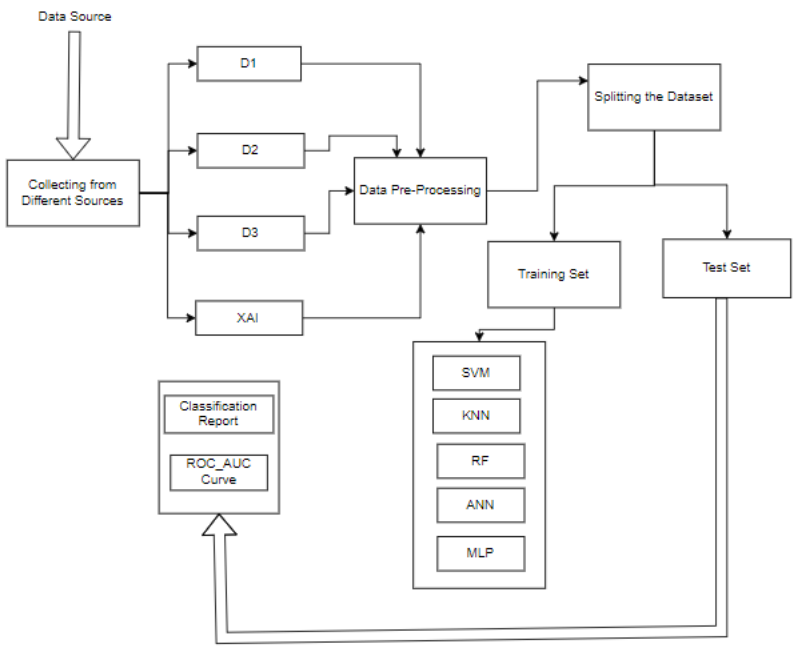



**Figure 1: Research Methodology Architecture**

## 3.6 Comparative Analysis

A benchmark examination is performed to compare the execution of diverse machine learning calculations. This investigation centers on recognizing the qualities and restrictions of each calculation within the setting of prescient support. Variables such as computational proficiency, demonstrate complexity, and appropriateness for diverse sorts of preservation information are considered.

# 4 Design Specification

This inquiry could be a multifaceted approach to prescient support within the fabricating segment, utilizing unused machine-learning strategies and information-handling approaches (Pech et al., 2021). The preparation of an expansive sum of mechanical information and the utilization of different machine learning models chosen for their capacity to anticipate machine disappointments is the centre of this inquiry. Data pre-processing steps have been thoroughly followed for cleaning the data that is suitable for the machine learning models.

Support Vector Machine (SVM), Multilayer Perceptron (MLP), Random Forest (RF), and Artificial Neural Network (ANN) are the chosen models for this inquiry. Depending on whether the information conveyance is direct or non-linear, the SVM show can be utilized with or without gamma adjustment. One neural arrangement that's especially great at recognizing complex designs in information is the multi-layer perceptron (MLP) classifier (Parikh et al., 2019). To maintain a strategic distance from repetition and increment expectation precision, RF Coach employments an outfit learning strategy joining different choice trees. ANN models are exceptionally valuable for finding nonlinear connections in information sets since they are built with numerous thick layers and actuation capacities.

This is about the employment of a comprehensive set of measurements for demonstrating assessment, counting disarray framework, review, F1 score, classification report, and exactness. These measurements give a comprehensive appraisal of the show, showing where the show exceeds expectations and where it falls brief of non-mechanistic forecasts (Jimenez et al., 2020). The region beneath the bend (AUC) and the working run (ROC) play a critical part in the assessment. In a prescient upkeep environment where both great and awful come about are awful, these measurements give a quantitative reflection of the show. Capacity to recognize between non-rates at distinctive limits.

The python tool is used for designing of the machine learning models. The version of python used for the building the model and analysing the dataset is 3.11.

# 5 Implementation

The machine learning models selected for predictive maintenance is trained and tested using four datasets (D1, D2, D3, and D4) (Leukel et al., 2021). The usage stage incorporates information preparation, designing, demonstrating preparing, assessment, and reenactment utilizing different machine learning calculations.

## 5.1 Data Preprocessing and Feature Engineering:

- **D1:** In this data, first the missing values are checked and handled by dropping the rows that contains the missing values. There are some irrelevant columns are present which are also dropped like “Date”. The LabelEncoder is used for converting the categorical variables into numerical values. After, all these processes, the feature scaling is used.
- **D2**: This dataset went through an initial cleaning process to remove extraneous columns (including UDI, Product Number). It was introduced to improve datasets and predictive power. After that prepare the dataset for machine learning applications by handling missing values and applying unique encoding to the segment variables.
- **D3**: Just like the D2, other columns have been evacuated and modern highlights presented. For machine learning compatibility, the dataset was reprocessed to guarantee no lost values and accurately coded categorical factors.
- **D4**: Here is the usage UID; Make columns and arrange dataset for machine learning applications. The information set was improved by making modern factors and guaranteeing that existing factors were coded accurately.

## 5.2 Model Training and Evaluation:

- SVM Classification Model: A bolster vector machine show was prepared on each dataset without gamma adjustment. Show execution was assessed utilizing measurements such as perplexity framework and classification report. We moreover calculated ROC bends and AUC scores to get the demonstration and its execution.

- MLP Classification Model: A neural organized demonstration, Multi-Layer Perceptron Classifier, with covered-up layers and standard setups was learned. Execution is commonly evaluated utilizing perplexity networks, classification reports, ROC bends, and AUC scores.
- Random Forest Classifier: This gathering demonstration, which combines numerous choice trees, was prepared for each information set. Execution assessment is comparable to SVM and MLP models and clarifies their perceptive capabilities.
- Artificial Neural Network Model: The ANN show is built utilizing TensorFlow and Keras, with layers and hubs made for the dataset. Execution was assessed utilizing the same measurements as the other models.

### 5.3 Tools and Technologies Used:

- Python: It is the essential programming dialect utilized for usage and is known for its broad libraries and systems that handle information investigation and machine learning.
- Pandas and NumPy: Utilized for data manipulation and numerical computations.
- Scikit-learn: Employed for machine learning algorithms like SVM, MLP, and Random Forest, and tasks like data splitting, model training, and evaluation.
- TensorFlow and Keras: These libraries were used to build and train the ANN model, providing a deep learning framework for handling complex data structures.
- Matplotlib: This library was used for creating ROC curve plots, aiding in the visualization and interpretation of model performances.

## 6 Evaluation

The ML models have been implemented on four sets of data. These data are related to the machine failure in manufacturing industries. Different sets of ML algorithms are also implemented for different datasets and the obtained result of classification is described in this section.

### 6.1 Classification Algorithms with D1 Dataset

| Model | Accuracy | Precision (avg) | Recall (avg) | F1-Score (avg) | AUC-ROC |
|---|---|---|---|---|---|
| Random Forest | 100% | 100% | 100% | 100% | 1.0 |
| SVM | 100% | 100% | 100% | 100% | 1.0 |
| MLP | 99.3% | 99.5% | 99.5% | 99.5% | 0.9998 |
| ANN | 99.21% | 99.5% | 99% | 99% | 0.999 |

### 6.1.1 Random Forest Model

A very high accuracy is achieved with implementation of the RF classifier. The overall accuracy obtained for the model is 1.00. Also, the other performance parameter values are very high including the AUC_ROC score of 1.00. The model is showing an extraordinary performance and this may be due to the overfitting or underfitting of the model.

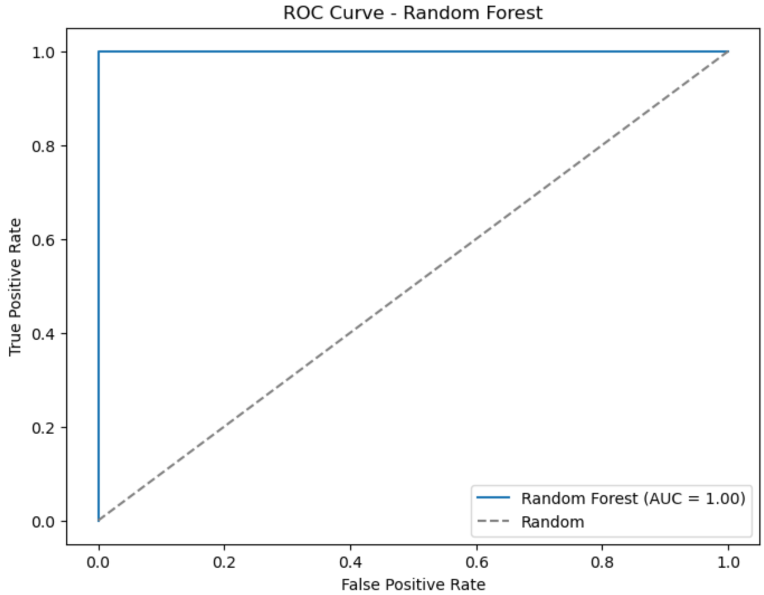



**Figure 2: ROC_AUC curve for Rand Forest Model**

### 6.1.2 Support Vector Machine

By utilising the SVM classifier, an exceptionally high level of accuracy is obtained. The overall accuracy of the model is 100%. The other parameters like precision, recall and F1 Score is also 1.

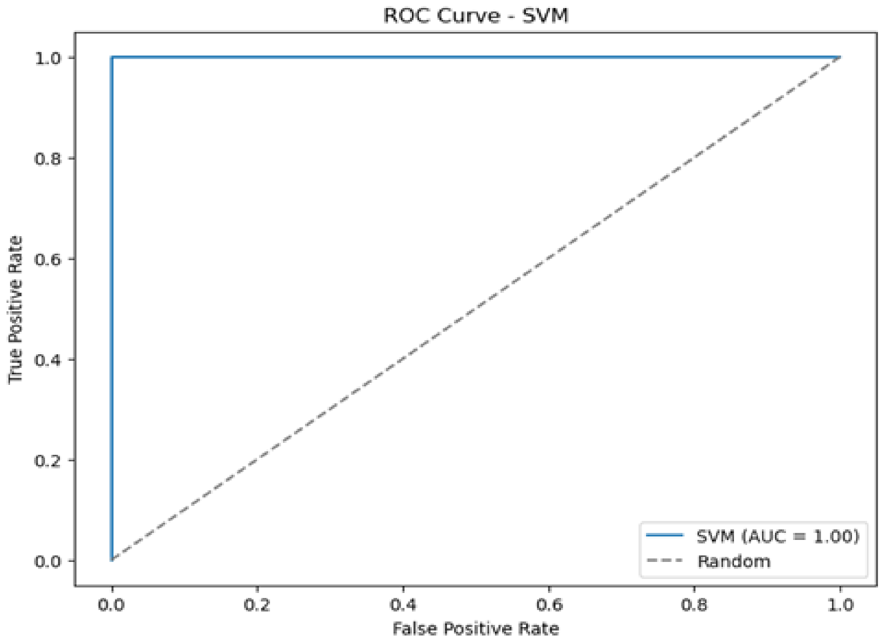



**Figure 3: AUC_ROC Curve for SVM model**

### 6.1.3 MLP Classifier

A good classification accuracy is obtained for the implementation of the MLP classifier. The overall accuracy obtained for the model is 0.99. Also, the other performance parameter values are also good including the AUC_ROC score of 1.00.

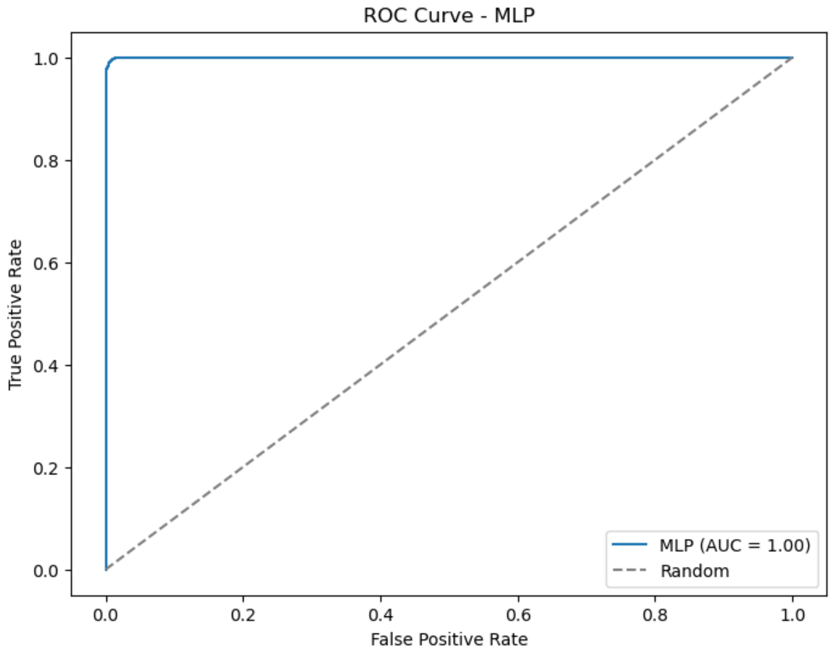



**Figure 4: AUC_ROC for MLP Classifier**

### 6.1.4 ANN (Artificial Neural Network)

By utilising the ANN classifier, an accuracy of 0.99 is obtained. The overall accuracy of the model is 99%. The other parameters like precision, recall and F1 Score is also 0.99.

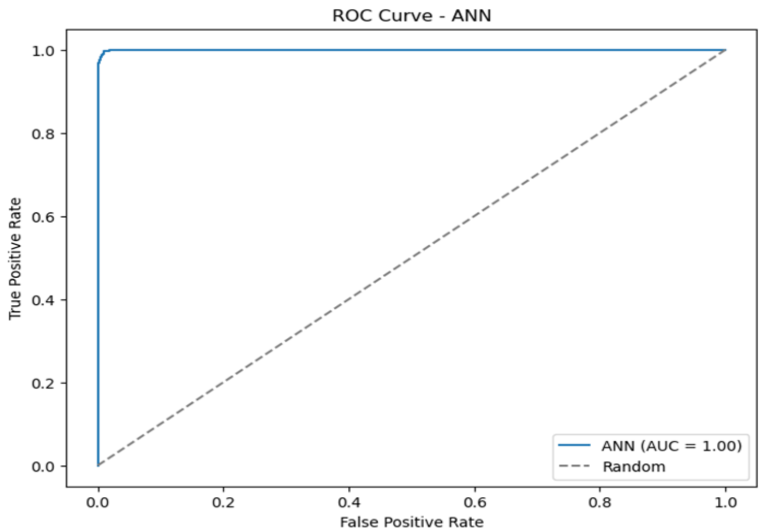



**Figure 5: AUC_ROC Curve for ANN**

## 6.2 Classification Algorithms with D2 Dataset

### 6.2.1 EDA of D2

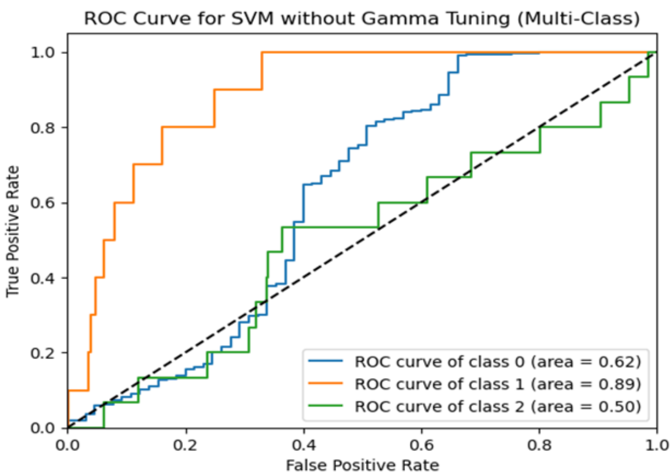
```
D2['Machine failure'].value_counts()

Machine failure
0      9661
1       339
Name: count, dtype: int64

D2['TWF'].value_counts()

TWF
0      9954
1        46
Name: count, dtype: int64

D2['HDF'].value_counts()

HDF
0      9885
1       115
Name: count, dtype: int64

D2['PWF'].value_counts()

PWF
0      9905
1        95
Name: count, dtype: int64
```

The above table is demonstrating the count of the different categorical variables in the data. The number of machines that are counted as not-failure is 9661 which is significantly higher than the number of the machines that are labeled as a failure.

| Models | Overall Accuracy |
|---|---|
| SVM | 0.97 |
| MLP | 0.97 |
| Ensemble (RF) | 0.99 |
| ANN | 0.54 |
| KNN | 0.97 |

### 6.2.2 SVM Classification Model

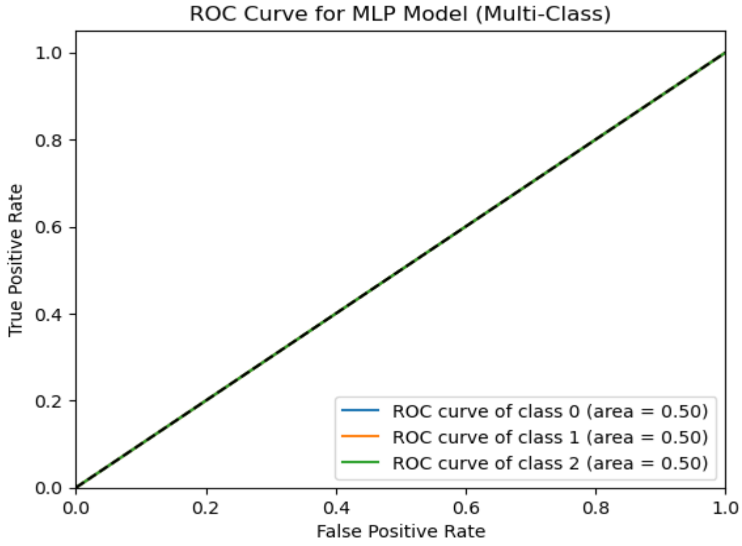
The classification report of the SVM classification model shows an overall accuracy of 0.97 which is quite a good classification accuracy to detect the machine that likely to be a failure in the manufacturing industry (Bharatiya, 2023). The other parameters of performance such as precision, recall, and F1 score are also quite good.
The AUC score of the model is varying from 0.50 to 0.89.



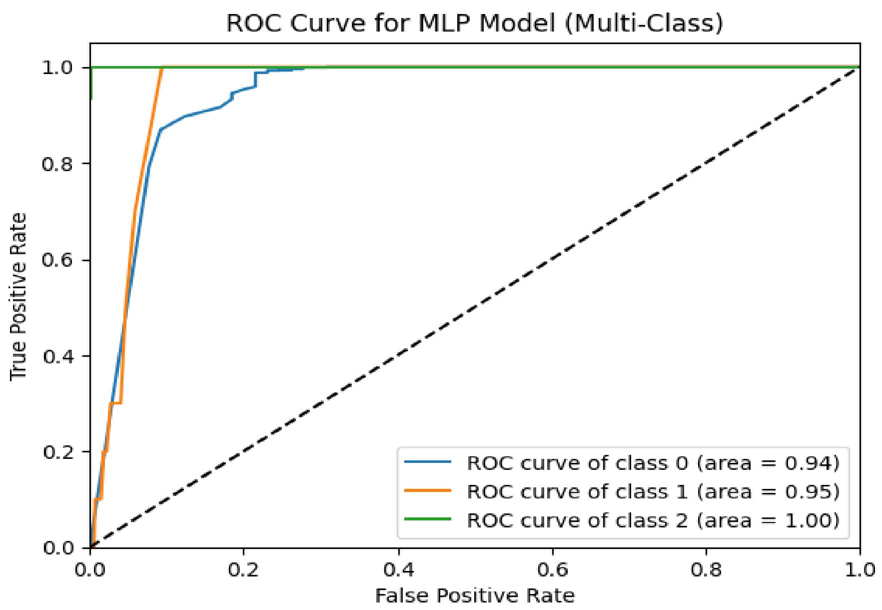
### 6.2.3 MLP Classification Model

Similar to the SVM classifier, the MLP classifier is also performing well as shown in the above classification report. The overall accuracy of classification for the model is 0.97 with the other parameter values such as precision, recall and F1 Score are 0.94, 0.97 and 0.95 respectuvely.

The AUC score for the classes in the classification are low and equal to 0.50.



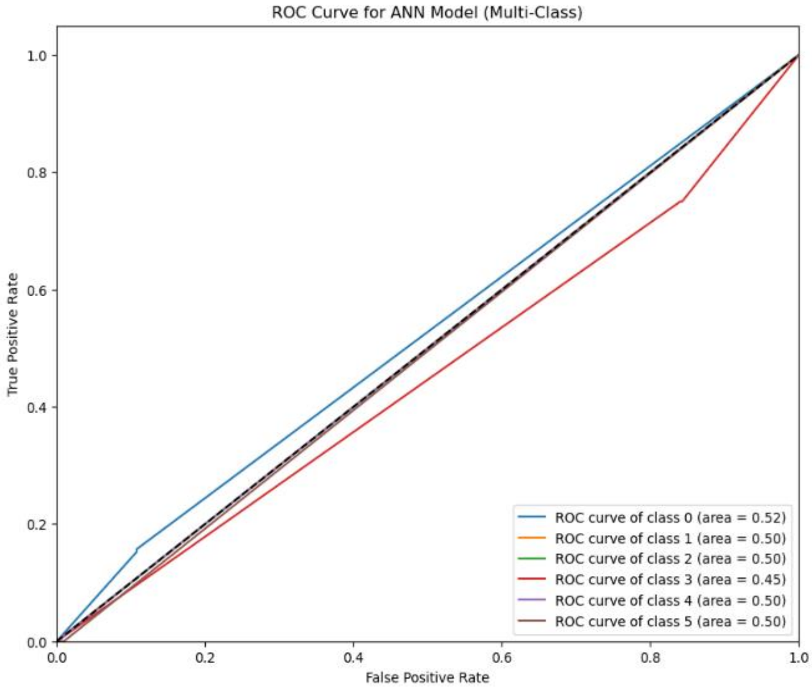

### 6.2.4 Ensemble Mode Using RF



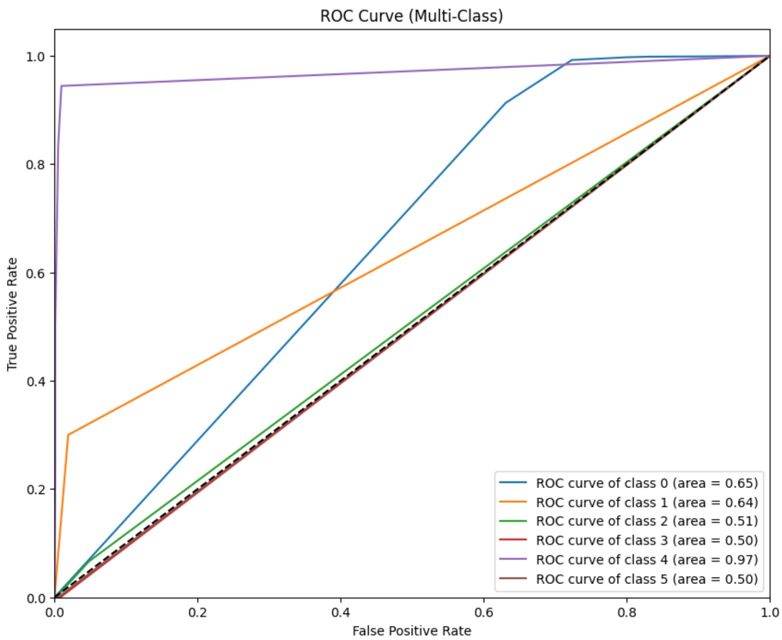

The classification resport of the RF classification model is showing an overall accuracy of 0.99 which is quite good classification accurcay to detcet the machine that likely to be failure in manufacturing industry. The other parameters of performance such as precision, recall and F1 score are also quite good.

### 6.2.5 ANN Classification Model

The classification report of the ANN classification model shows an overall accuracy of 0.54 which is poor classification accuracy to detect the machine that is likely to be a failure in the manufacturing industry. The other parameters of performance such as precision, recall, and F1 score are also poor.




### 6.2.6 KNN Classification Model



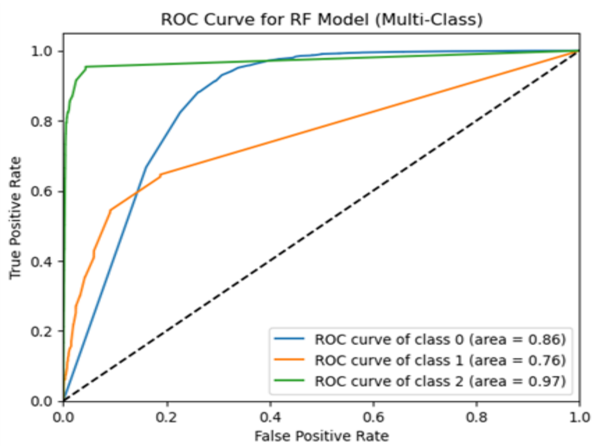

The classification resport of the KNN classification model shows an overall accuracy of 0.97 which is good classification accuracy to determine the machine that is likely to be a failure in the manufacturing industry. The other parameters of performance such as precision, recall, and F1 score are also good.

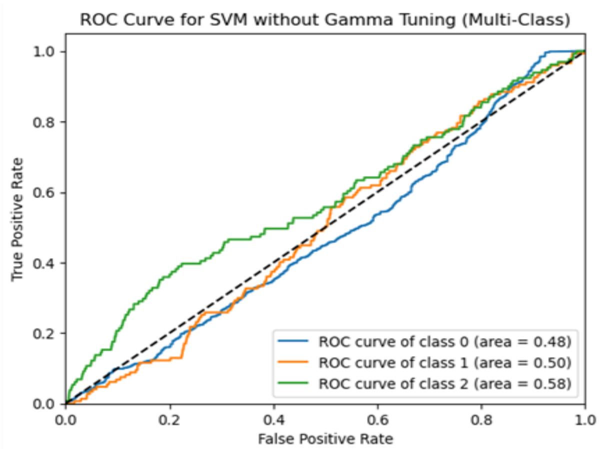
**Comparison of Models**

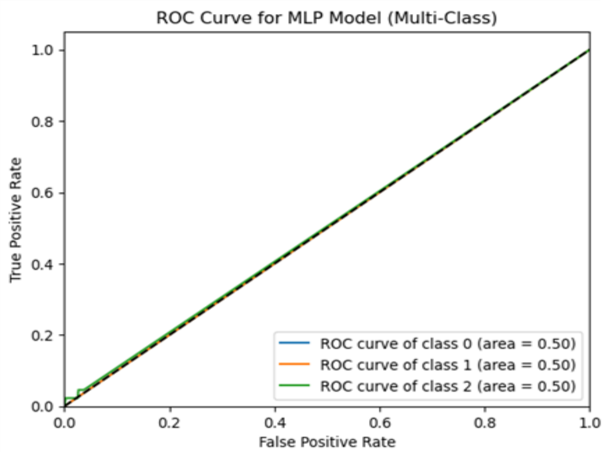
## 6.3 Classification Algorithm with D3 Dataset

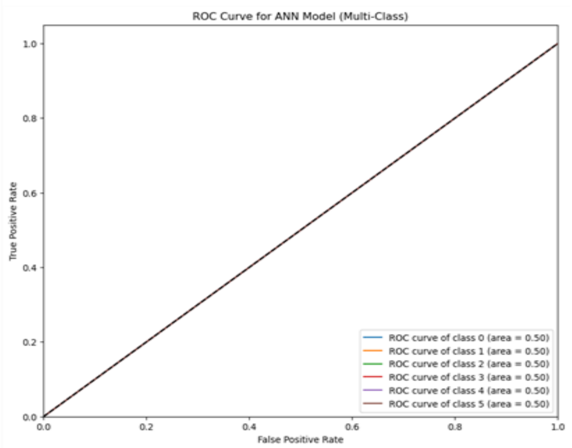
Only two classifiers are used in the case of the D3 dataset. The classification models designed for the D3 dataset are Random Forest and the SVM classifier. The results of each of the models are as follows

| Model | Overall Accuracy | Precision | **Recall** | **F1 Score** |
|---|---|---|---|---|
| SVM (D3 Dataset) | 0.98 | 0.96 | 0.98 | 0.97 |
| Random Forest (D3 Dataset) | 0.98 | 0.96 | 0.98 | 0.97 |
| MLP | 0.98 | 0.98 | 1 | 0.99 |
| ANN | 0.98 | 0.98 | 1 | 0.99 |
| | | | | |



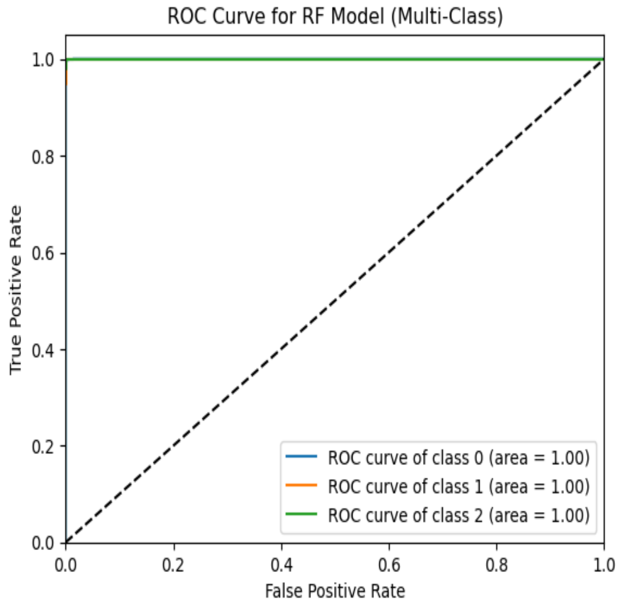



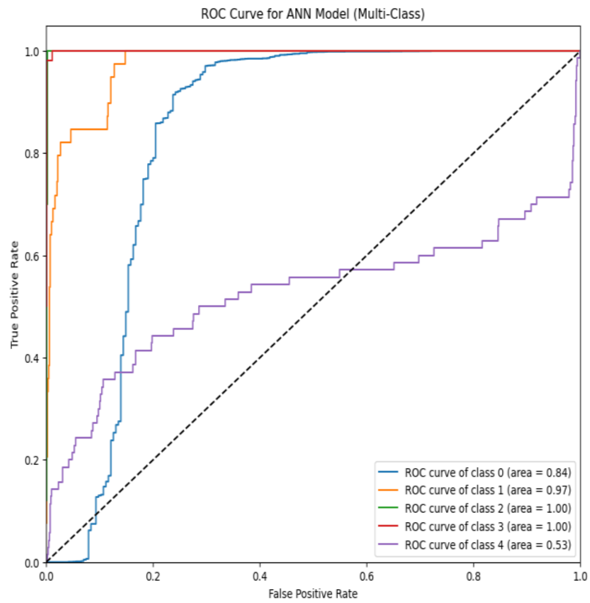



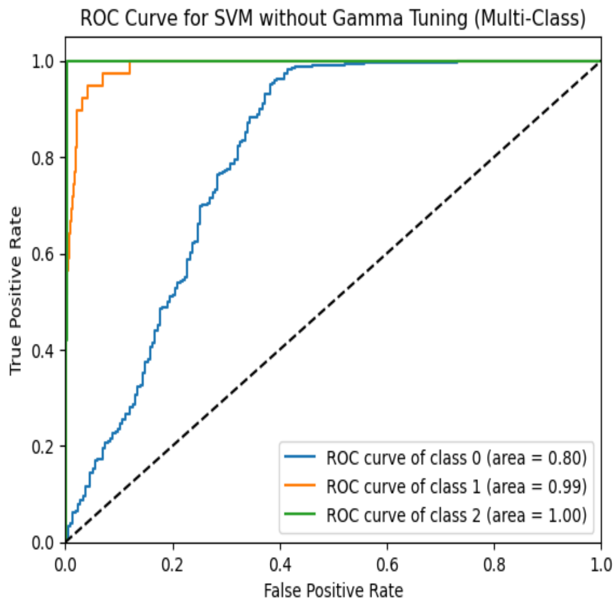
With D3 dataset, the SVM classifier which is classification algorithm is demonstrating a quite good value of classification accuracy. The obtained classification accuracy is 0.98 that means among 100 new test instances the model is able to predict 98 classes correctly. The other performance metrics values are also quite good which are 0.96 for precision, 0.98 for recall and 0.97 for f1-score.
The ensemble bases RF classifier (a classification algorithm) is showing a respectable value of classification accuracy with the D3 dataset. A classification accuracy of 0.98 was achieved, which indicates that out of 100 new test examples, the model correctly predicted 98 classes. Values of 0.96 for precision, 0.98 for recall, and 0.97 for f1-score are among the other excellent performance indicators.

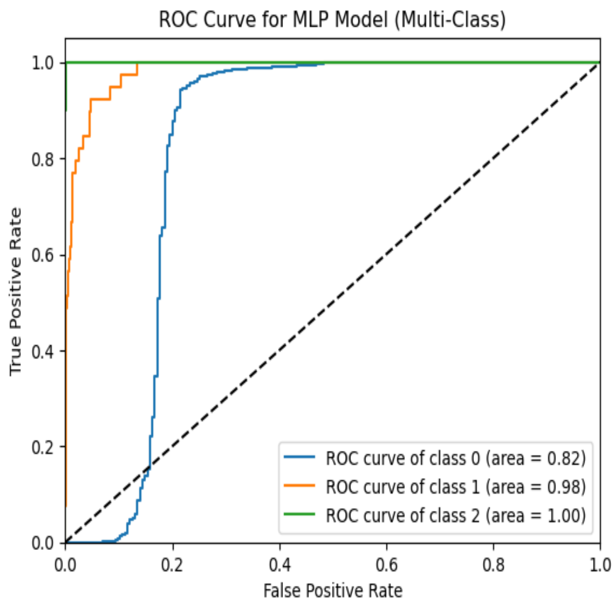
## 6.4 Classification Algorithm on XAI Drilling Dataset

| Class | SVM Precision | SVM Recall | MLP Precision | MLP Recall | RF Precision | RF Recall |
|---|---|---|---|---|---|---|
| Class 0 (No Failure) | 0.96 | 1.00 | 0.97 | 1.00 | 1.00 | 1.00 |
| Class 1 (BEF - Bearing Failure) | 0.00 | 0.00 | 1.00 | 0.05 | 0.95 | 0.97 |
| Class 2 (CCF - Chisel Edge Failure) | 0.00 | 0.00 | 0.91 | 0.96 | 1.00 | 0.96 |
| Class 3 (FWF - Flank Wear Failure) | 0.96 | 0.96 | 0.92 | 1.00 | 1.00 | 1.00 |
| Class 4 (WDF - Wear Detected Failure) | 0.00 | 0.00 | 0.00 | 0.00 | 1.00 | 0.97 |




### Support Vector Machine (SVM) without gamma tuning

The SVM model, in this case, did not perform well for classes 1, 2, and 4, as indicated by a precision and recall of 0. This suggests that the model could not correctly identify any instances of these classes. However, it performed quite well for class 0, with a precision and recall of 0.96, and class 3, with a precision and recall of 0.96.

### Multi-Layer Perceptron (MLP)

The MLP model showed an improvement over the basic SVM for some classes. It achieved a perfect score for class 3, and its performance on class 2 was also good with a precision of 0.91 and a recall of 0.96. The performance on class 1 and class 4 was still lacking.

**Random Forest (RF):**

The RF classifier showed superior performance compared to the other two models, with near-perfect precision and recall for all classes. It seems to handle the multi-class classification problem very well.

The Random Forest classifier demonstrated robustness across all classes, as it achieved high precision and recall for each class (Van Calster et al., 2019). In contrast, SVM and MLP had some difficulties with specific classes, particularly the minority classes (1 and 4), which could be due to class imbalance or other factors such as the features not being discriminative enough for those classes.

## 6.5 Discussion

The exploration of machine learning algorithms for predicting machine failures in manufacturing industries reveals significant advancements and some limitations. The studies conducted across various datasets (D1, D2, D3, and XAI Drilling Dataset) show that while algorithms like MLP and RF can achieve high accuracy (up to 99.4% and 99% respectively), the performance heavily relies on the quality of data preprocessing, feature engineering, and model selection, as highlighted by Assagaf, Sukandi, and Abdillah (2023).

The SVM's inability to correctly classify minority classes points to potential issues in class imbalance, which could be mitigated by techniques such as oversampling or more sophisticated feature selection methods. MLP and RF's stronger performance suggests that more complex patterns are captured, but the poor performance of ANN indicates possible issues with the network architecture or data representation.

The results should be contextualized within the broader narrative of AI for predictive maintenance (Fernandes et al., 2019). The literature review suggests that while deep learning provides nuanced predictions, it also presents challenges in interpretability and requires substantial data quality and volume, as deep learning models are data-hungry and complex.

To improve the experimental design and results, future work could include:

- Implementing more robust data preprocessing methods to handle class imbalance and noise.
- Exploring alternative neural network architectures that might better capture the complexities of the data.
- Incorporating ensemble methods that combine different model predictions to improve accuracy and robustness.
- Conducting experiments with varied hyperparameter tuning to establish the best model configurations.

# 7 Conclusion and Future Work

This study set out to assess how well machine learning algorithms perform in predictive maintenance for the industrial sector, with the ultimate goal of making manufacturing processes more dependable and productive. We evaluated various machine learning algorithms, with an emphasis on feature engineering and selection strategies, to see which ones could improve the model's performance. The study's secondary aim was to assess how decision-making is affected by uncertainty in predictive maintenance models.

The results show that algorithms such as Random Forests (RF) and Multi-Layer Perceptrons (MLP) perform very well, with an accuracy rate of up to 99.4 percent. Based on the findings, it appears that RF and MLP are the most popular algorithms, which answers RQ1. If you use clever data pretreatment and good feature engineering, your RQ2 model will perform much better. Uncertainties in predictive maintenance models considerably affect decision-making, according to the study (Research Question 3), particularly in regards to data quality and class imbalance.

The research still had to overcome a number of challenges, such as the need for massive datasets and the difficulty of understanding complex model outputs, despite these promising results.

Incorporating domain information to enhance feature selection and making models more understandable might be the subject of future research. A potentially lucrative business opportunity may arise from the development of user-friendly predictive maintenance software that incorporates such algorithms. Hybrid models that combine the best features of several algorithms with real-time data streams should be the focus of future studies in order to greatly enhance forecast.

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