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Enhancing Industrial Reliability through Predictive Maintenance using Hybrid ML-DL Models

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***Abstract* –** This study Predictive maintenance seeks to anticipate equipment breakdowns and reduce unplanned downtime through the utilization of sensor data and sophisticated modeling techniques. This study introduces a detailed pipeline utilizing the AI4I 2020 Predictive Maintenance Dataset, a high-caliber synthetic industrial dataset that includes air and process temperatures, rotational speed, torque, tool wear, and failure labels from the UCI Machine Learning Repository. Our methodology includes thorough preprocessing, which involves the elimination of inaccurate measurements, the generation of engineering characteristics such as temperature difference and mechanical power, feature standardization, and stratified train-test division. Class imbalance is mitigated using SMOTE, which equalizes the proportion of failure and non-failure cases. We develop and enhance various machine learning models (Random Forest, XGBoost, SVM, Logistic Regression) and a Conv1D deep learning model specifically designed for sequential sensor data. Model performance is assessed using metrics like accuracy, precision, recall, F1-score, ROC-AUC, and log loss. Results indicate that Random Forest and XGBoost achieve good accuracy and balanced detection, whereas SMOTE markedly improves recall. The Conv1D network demonstrates significant vulnerability to failures, especially when class balancing is implemented. The innovation consists of combining domain-specific feature engineering with sophisticated oversampling methods and evaluating machine learning and deep learning algorithms on a practical maintenance dataset. Future endeavors will concentrate on implementing the model in real-time industrial settings, investigating hybrid architectures that integrate interpretability with sequential pattern learning, and assessing model robustness using live maintenance data.

Keywords- Predictive Maintenance**,** Convolutional Neural Network (Conv1D)**,** Machine Learning and Deep Learning**,** Industrial IoT (IIoT) and Rotating Machinery Fault Detection.

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1. Introduction

The steel industry is one of the biggest and most energy-intensive in the world. It depends on rotating machines like motors, pumps, fans, turbines, compressors, and gearboxes to keep running all the time. These machines are the backbone of production processes because they keep materials and energy flowing without stopping. However, these machines are very likely to break down unexpectedly because they are used in harsh conditions, carry heavy loads, vibrate, and get hot. This not only stops production, but it also costs a lot of money, puts people at risk, and makes operations less efficient. In steel plants, traditional maintenance methods like reactive maintenance (where repairs are made after a failure) or preventive maintenance (where servicing is done on a regular basis no matter what the equipment's actual condition is) often don't work and cost too much because they either don't stop unplanned downtime or they cause unnecessary maintenance work. In this situation, predictive maintenance (PdM) has become a game-changing method that uses the combination of Internet of Things (IoT) technologies and advanced machine learning algorithms to predict when equipment will break down before it happens. This makes maintenance schedules more efficient, cuts down on downtime, lengthens the life of machines, and keeps production going without a hitch. IoT-enabled sensors can be put on spinning machinery to collect, send, and store a steady stream of real-time data, like vibration signals, temperature measurements, noise emissions, lubrication content, and electrical parameters [1]. This is the first time we've ever been able to see how well the machines are performing. When you combine this vast amount of machine data with machine learning approaches, you can uncover little patterns and strange things that could be signals of issues before they emerge. Traditional monitoring systems might not be able to do this. Support Vector Machines, Random Forests, gradient boosters, and deep networks are examples of machine learning models that can work with complicated multifaceted sensor data, find non-linear relationships, and offer accurate predictions about the remaining useful life (RUL) and prospective failure mechanisms of rotating equipment. Preventive maintenance in steel plants not only makes the equipment more reliable, but it helps the plants accomplish their goals for energy efficiency, resource optimization, and sustainability by reducing waste, downtime, and better production planning [2]. The Industry 4.0 paradigm has also made it easier to use smart manufacturing solutions. These technologies utilize AI, IoT, and big data analytics to create smart decision-making systems that can adapt in real time. Predictive maintenance that uses machine learning, the Internet of Things, and others is very helpful for fixing problems like uneven load distribution in rolling mills, induction motors that get too hot, pumping systems that have bearing failures, coupled with blowers that vibrate too much in steel plants, where retaining things running smoothly is very important. If these flaws aren't found, they can lead to very bad system failures. As high-frequency IoT sensor data becomes more common, it's increasingly vital to use advanced feature extraction and signal processing methods, like time-domain, frequency-domain, and time–frequency analyses. This makes sure that AI algorithms are trained on features that are useful & representative, which makes fault classification and prediction more accurate. Making a good preventative care model for rotating machines in steel plants is hard, even though it has a lot of potential. This is because it has to deal with noisy and high-dimensional data, make sure that multiple Internet of Things (IoT) devices can work together, manage large-scale data storage, or deal with privacy and cybersecurity issues. In addition, real-world industrial environments often deal with changing operational circumstances, changing loads, and outside interruptions. So, it is important to create machine learning models that are strong, flexible, and able to transfer knowledge between different types of machines and ways of doing things [3], [4]. Recent advancements in deep learning architectures, like as Convolutional Neural Networks (CNNs) for analyzing signal vibration and Recurrent Neural Networks (RNNs) for modeling temporal data, indicate interesting methods to enhance the precision and reliability of predictions. Hybrid methods that combine algorithmic learning with models grounded in physics or mathematical techniques can also provide both domain knowledge and data-driven insights. This could make predictive maintenance platforms easier to understand and use in more situations [5]–[7]. There are additional economic benefits to using scheduled upkeep in steel factories. For example, optimized maintenance plans can save businesses 20–30% on maintenance expenses, minimize downtime for machinery by up to 50%, and make equipment live longer. This gives organizations an edge in an industry where dependability and effectiveness are particularly crucial. Predictive maintenance also helps with ecological objectives by saving energy, cutting emissions from machines that aren't working right, and making machinery last longer, which is part of the circular economy. This work focuses on developing a predictive maintenance approach for rotating machinery in steel production plants, using sensor data from the Internet of Things (IoT) and machine learning techniques. The goal is to create an intelligent framework that makes it easier to find problems early, accurately predict when machines will break down, and give useful maintenance tips. The research augments the current understanding of industrial AI applications by analyzing various IoT-based data acquisition methods, initial processing techniques, feature extraction strategies, and training models, while specifically addressing the unique challenges and demands of steel plant environments [8], [9]. The study also emphasizes that models must be comprehensible, scalable, and compatible with existing maintenance systems to be used in practical scenarios. In the end, building these kinds of maintenance planning models will probably revolutionize how upkeep is done in steel facilities. This will lead to better operations, savings, more safety, and a move toward smart, sustainable, and resilient manufacturing systems.[10]. In manufacturing, especially in steel plants, rotating equipment like motors, pumps, compressors, and air turbines are very important to the production process. For this reason, it is very important that industrial machinery works well to keep productivity high and prices low. Unplanned downtime caused by a machine breaking down can cost a lot of money, slow down production, and make the workplace less safe. Common maintenance methods, like reactive maintenance or preventive maintenance, don't always work well to solve these problems. Reactive maintenance, which means fixing equipment only after it breaks down, leads to unexpected downtime and high repair costs. Preventive maintenance, on the other hand, is both costly and inefficient because it doesn't take into account how well the machinery is working. The Industrial Internet of Things (IIoT) and the affordability of large-scale sensor data have made predictive maintenance a game-changing method. It lets you predict when machines will break down and change maintenance schedules based on how the machines are actually working. Predictive maintenance uses IoT-enabled sensors to keep an eye on important machine parameters like vibration, pressure, and temperature, and rotational speed all the time. It collects high-resolution data that shows how well rotating machinery is working [11]. When paired with advanced machine learning methods, this data can be used to make predictive models that can find early symptoms of wear, degradation, or failure patterns. This makes it easier to undertake maintenance when it's needed and reduces unplanned downtime.[1], [12]. Machine learning approaches, including supervised learning algorithms such as Support Vector Machines (SVM), Random Forests, and Artificial Neural Networks (ANN), can effectively analyze complex and nonlinear relationships between sensor measurements and machine health indicators. Additionally, unsupervised learning methods, such as clustering and anomaly detection algorithms, can identify abnormal behavior in machines without requiring labeled failure data, which is often limited in industrial settings. In a steel plant context, the implementation of predictive maintenance models for rotating machines not only ensures continuity in production but also enhances safety, optimizes resource allocation, and extends the operational lifespan of expensive equipment. Furthermore, integrating IoT infrastructure with machine learning-based predictive analytics allows plant managers to make data-driven maintenance decisions, reduce unnecessary downtime, and improve overall plant efficiency[13]–[15]. Even though these are good things, problems like data quality, sensor calibration, computing needs, and model interpretability need to be properly solved in order to make sure that forecasts are accurate. This study intends to establish a predictive maintenance plan for rotating machines in a steel factory setting by leveraging IoT-generated information as well as sophisticated algorithms for machine learning [16]. The proposed model will focus on getting real-time operational parameters, using strong algorithms to process and analyze the data, and giving useful information to prevent machine failures. This will make operations more reliable, lower maintenance costs, and help with the long-term and efficient administration of industrial assets.

1.1 Background and Contextual Framework

1.1.1 Historical Overview and Evolution of the Topic

In factories, maintenance has moved from only mending machines when they break down to using data and being more proactive. When essential rotating parts like motors, pumps, and air turbines break down without warning in steel mills, it can cause output losses and high maintenance costs. In the middle of the 20th century, people started doing preventive maintenance. It used planned inspections and replacing parts to cut down on failures. It worked effectively, but it didn't always take into consideration how the machines were operating at the moment, which meant that repair was often needed [17]. The Industrial Internet of Things (IIoT) made it feasible to constantly keep an eye on things like movement, temperature, when rotational speed, which provided a lot of operational data. At the same time, machine learning algorithms helped us look at this data, discover flaws, and make educated guesses about when things might go wrong. By using IoT and machine learning together, maintenance has gone

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from being reactive to being predictive. This has made steel mills more efficient, decreased money, and made essential machines last longer [18], [19].

1.1.2 Relevance to Current Research Landscape

The need of creating maintenance predictions models for machines that spin in steel plants is growing as more and more businesses use Industry 4.0 technologies to make their operations more efficient. Conventional maintenance methods, including reactive and preventive tactics, are inadequate for contemporary industrial requirements as they fail to consider real-time machinery conditions, frequently leading to expensive downtime and poor resource utilization. Recent studies stress the importance of using IoT-enabled sensors to gather ongoing operational data and machine learning methods to analyze it for predictive insights Such approaches enable early detection of faults, optimized maintenance schedules, and reduced unplanned failures. In steel plants, where rotating machinery is critical for uninterrupted production, predictive maintenance research addresses both economic and safety concerns. Current studies focus on combining data-driven analytics with industrial operations, making this research highly relevant for advancing intelligent maintenance systems and contributing to the broader field of smart manufacturing and industrial IoT applications.

2. Literature Review

Choi 2023 et al. Develops a tap temperature prediction model (TTPM) utilising machine learning-based support vector regression (SVR) to make electric arc furnaces (EAFs) more efficient in the steel sector. Six machine learning algorithms were trained on operational data from a stainless EAF. SVR did the best job, getting an RMSE of 20.14 and handling noisy features well. The device cut the difference in tap temperature by 17% and the average power use by 282 kWh per heat over five months. The internal rate of return was 35.8% based on an economic analysis. The TTPM's successful ten-month operation shows that it is reliable, which improves production efficiency, saves energy, and helps steel manufacturing become carbon neutral[20].

Shaheen 2023 et al. Creates a machine learning-based method to guess the mechanical properties of high-strength steel (HSS) plates at high temperatures, such as ultimate tensile strength, yield strength, 0.2% proof strength, and elastic modulus. Conventional approaches employing design code reduction factors frequently neglect the impact of testing methodologies, manufacturing techniques, and chemical composition, resulting in erroneous forecasts. To solve this problem, a deep neural network model is trained with experimental data from the literature, employing temperature and chemical composition as input variables. The results show a strong association and a small prediction error, making it a useful tool for making sure that HSS constructions are safe from fire and can handle high temperatures[21].

Radonjić 2022 et al. Modern predictive maintenance benefits from IoT solutions that simplify data collection and analysis, while AI-driven algorithms combined with interconnected sensor architectures create intelligent maintenance systems that surpass traditional approaches. Propose an acoustic-based IoT system for detecting conditions in rotating machines. The device is mobile, cost-effective, and employs a discrete wavelet transform with neural networks, tuned using a genetic algorithm. Tested in real industrial environments with heavy acoustic interference, the system achieved strong results, reaching an average F1 score of 0.99 with optimized hyper parameters, demonstrating its reliability, scalability, and practical effectiveness in predictive maintenance[22].

Redchuk 2022 et al. Looks at how Canvass Analytics' platform is being used to implement a machine learning (ML) solution in steel manufacturing. It also talks about how AI/ML may improve traditional industrial processes. A bibliographic evaluation of the Scopus database set up the conceptual framework and the most up-to-date information. This was followed by a case study to see how a No-Code/Low-Code ML solution would affect the operations of a steel mill. The results showed that AI/ML can be made available to process operators by showing that it can be used faster and with better results than traditional analytics methods. The report stresses the need for smart manufacturing, data, and new business models that might make it easier and faster to use AI and ML in business[23].

Jamshidi 2021 et al. uses a mix of machine learning methods to guess how Oxide Precipitation Hardened (OPH) alloys, a new type of Oxide Dispersion Strengthened material, would behave mechanically. Traditional analytical modelling has a hard time with the alloys' many variables, nonlinearities, and uncertainties. AI-based methods work better in these cases. We used three methods to find the ultimate tensile strength (UTS) and elongation: feedforward neural networks trained with particle swarm optimisation, and two adaptive neuro-fuzzy inference systems that used fuzzy C-means and subtractive clustering. Using experimental tensile data from mechanically alloyed and heat-treated OPH variants, the models achieved about 95% accuracy, which made it possible to reliably predict properties based on composition and processing parameters. This also generated it possible to make alloys with out requiring to do any math.[24].

TABLE 1 LITERATURE SUMMARY

Authors/year	Methodology	Research gap	Findings
Mey/2020 [25]	Vibration-based machine learning fault detection.	Limited studies on robust, scalable predictive maintenance models for rotating machinery.	Fully connected neural network achieved highest accuracy in vibration fault detection.
Sheu/2020 [26]	Deep learning-based sheet metal identification.	Existing automation lacks accuracy in sheet metal part identification systems.	IDS-DLA achieved higher accuracy than previous sheet metal identification benchmarks.
Sepulveda/2020 [27]	Optimized vibration-based fault diagnosis model.	VML models lack generalization across machines and	Optimized VML model showed robust, reliable fault

		varying operating conditions.	detection across conditions.
Huang/2020 [28]	CNN-based steel wire rope detection.	Conventional methods rely on manual features, limiting detection accuracy.	CNN-based method outperformed traditional approaches in accuracy and speed.
Masani/2019 [29]	CART-based production machine accuracy prediction.	Lack of automated systems predicting machine accuracy with energy data.	CART model accurately predicted machine performance and generated power reports.
Fucun/2018 [30]	CART-based approach improved machine accuracy prediction and automated power reporting.	Existing studies lack integration of machine accuracy prediction with automation.	Proposed system achieved accurate machine monitoring with automated reporting.
[31]	CNN-based CWTS fault diagnosis method.	Traditional vibration methods miss crucial information; CNN-CWTS improves accuracy.	CNN-CWTS method accurately diagnoses faults across different rotating machinery.
Sarkar/2017 [32]	Text mining-based accident prediction model.	Limited research on text-driven accident prediction models in steel industry.	Maximum Entropy and Random Forest achieved highest accuracy in predictions.
Layouni/2017 [33]	Wavelet-ANN based defect detection.	Manual MFL analysis is time-consuming and error-prone for operators.	Proposed method accurately detects defect length and predicts depth efficiently.
Kande/2017 [34]	Plant-wide rotating machine monitoring methodolog	High monitoring costs limit plant-wide implementation of condition monitoring systems.	Advancements in sensing and automation can enable broader condition monitoring.

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3. Research Methodology

This study utilizes a research methodology designed to provide a comprehensive predictive maintenance framework through the application of machine learning (ML) alongside deep learning (DL) techniques, leveraging the AI4I 2020 Predictive Maintenance set from the UCI Machine Learning Repository. The methodology delineates a structured pipeline that initiates with raw data acquisition and progresses through preprocessing, exploratory data analysis (EDA), model development, and performance assessment. The dataset includes a variety of sensor readings that are relevant to machine conditions and operating parameters, making it suitable for the failure prediction task. The first step is to do a lot of preprocessing because industrial sensor data often has noise, values that are incorrect, and other problems. This means finding and fixing missing data, getting rid of measurements that don't make sense (such negative torque or axial speed), and creating attributes that are specific to the field, including temperature differential or mechanical power. The new attributes improve the feature space and capture important trends of machine health. All of the chosen qualities are standardized so that the contributions of each variable are equal. Stratified sampling is then used to split the dataset into training and testing subsets, keeping the same number of failure and non-failure occurrences in each. Since machine failures don't happen very often in factories, the study uses the Synthetic Minority Oversampling Technique (SMOTE) to fix class imbalance. SMOTE makes fake examples of the minority class, which stops learning algorithms from selecting cases where there is no failure. After preprocessing, an exploratory data analysis (EDA) step provides statistical and visual insights into feature distributions, correlations, and patterns that distinguish functioning equipment from failing equipment. This step helps choose a model and points out any problems. Both machine learning models (Random Forest, XGBoost, SVM, and Logistic Regression) and a deep learning Conv1D model are built and improved through hyperparameter optimization. We carefully evaluate their performance using standards like accuracy, precision, recall, F1-score, ROC-AUC, and log loss to make sure that the comparison test is fair.

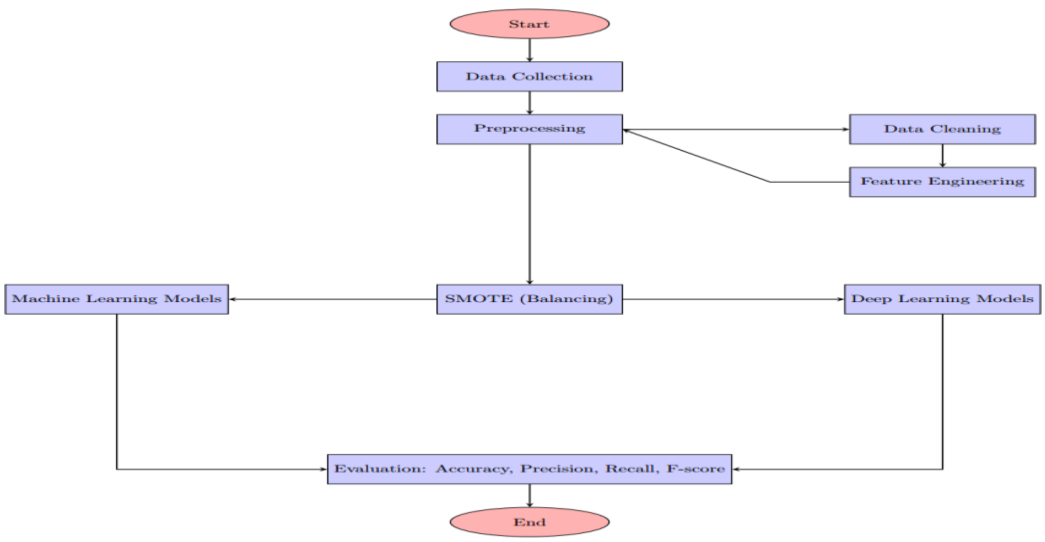

Figure 1 Proposed Flowchart

3.1 Dataset Description

This study utilizes the AI 4I 2020 Predictive Repair Dataset available from the repository of UCI Machine Learning. The dataset has sensor readings and information about how the machine works, such as the temperature of the air and the process, the speed of rotation, the torque, the wear on the tool, and the labels for machine failures. It provides a realistic industrial environment for maintenance planning research, incorporating several variables to precisely characterize machine deterioration and pinpoint operational phases.

3.2 Data Preprocessing

Preparing the data is a crucial step in building a good predictive maintenance model since it makes sure that the data is accurate, consistent, and suitable for training deep learning and machine learning algorithms. The process begins by looking at and dealing with missing values in all of the variables. Lack of data can throw off statistical distributions and make models less reliable, thus the dataset is carefully checked for any problems. Sensor accuracy is very important for predictive maintenance. If there is missing data, it is either filled in with the right methods or the affected records are deleted if the amount of missing data is little. The next step is to get rid of readings that don't make sense since they go against the physical limits of how machines work. Negative values for torque or rotational velocity are not possible and are seen as errors in the data. Removing these kinds of errors improves the quality of the dataset and stops false patterns from forming during model training. After that, feature engineering is done to add more useful attributes to the dataset. Two important factors are identified: Temp Difference (Temp_diff), which shows the difference between the temperature of the process and the temperature of the environment, and Mechanical Power (Power), which is calculated using torque and rotational velocity. These designed features give us better information on the health of machines and the stress they are under while they are running, making the dataset more like what we would find in the real world. After that, relevant features are selected based on their predictive importance and the knowledge of the field. The input features are things like air temperature, process temperature, rotational speed, torque, tool wear, temperature difference, and power. The objective variable is machine failure. Z-score normalization is used to standardize all the chosen features so that they may be compared across different scales. This sets the mean to zero and the variance to one. Stratified sampling divides the dataset into two groups: training and testing, with 80% of the data going to training and 20% going to testing. This makes sure that the number of failures and non-failures stays the same, which makes it easier to evaluate the model fairly.

3.3 Handling Class Imbalance (SMOTE)

The dataset shows that there are too many classes because machines don't break down very often. This could cause models to make predictions that are too optimistic. To fix this problem, the training set uses the Synthetic Minority Oversampling Technique (SMOTE). SMOTE generates artificial specimens of the minority failed class by the interpolation of the current examples, thus balancing class distributions. This ensures fair learning and improves the accuracy of models in predicting rare failures.

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3.4 Exploratory Data Analysis (EDA)

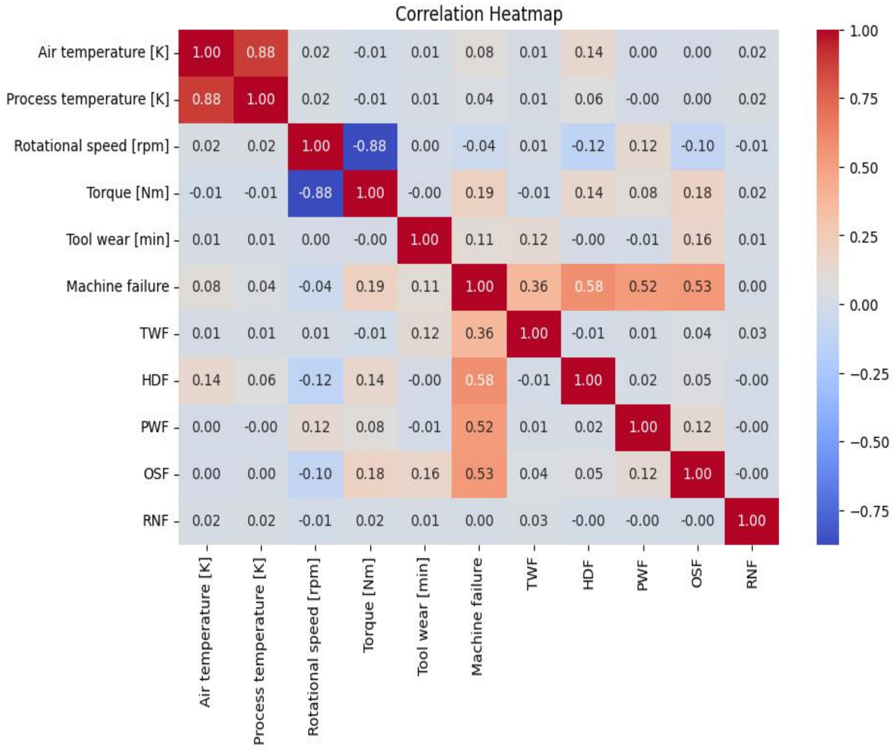

Figure 2 Correlation Heatmap

The heatmap shows strong correlation between air and process temperatures, negative torque-speed relation, highlighting influential parameters for machine failures.

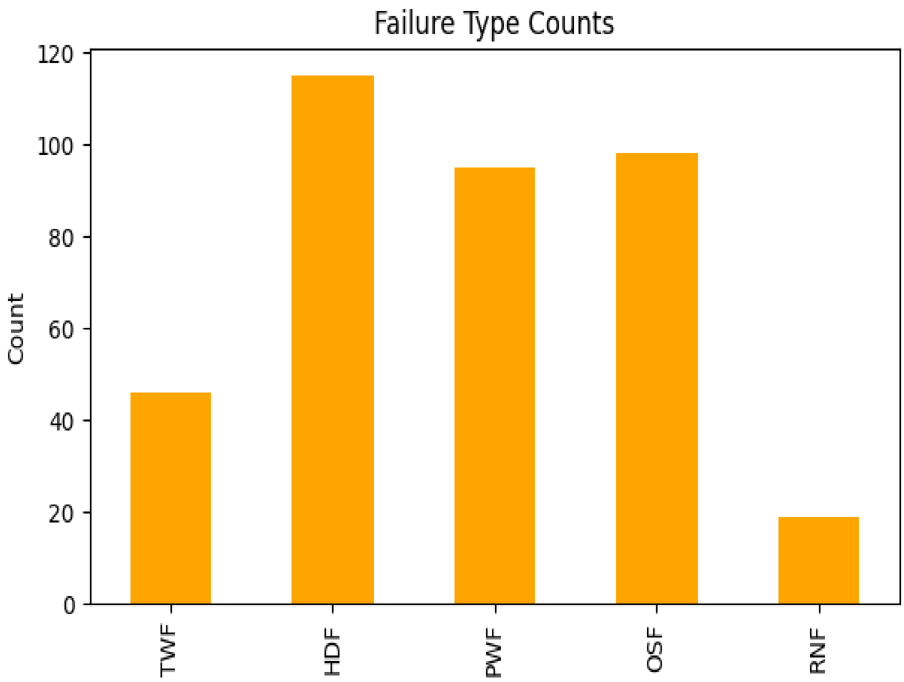

Figure 3 Failure Type Counts

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Failure count plot reveals imbalance: HDF and OSF dominate, RNF rare, emphasizing importance of balancing strategies like SMOTE for fairness.

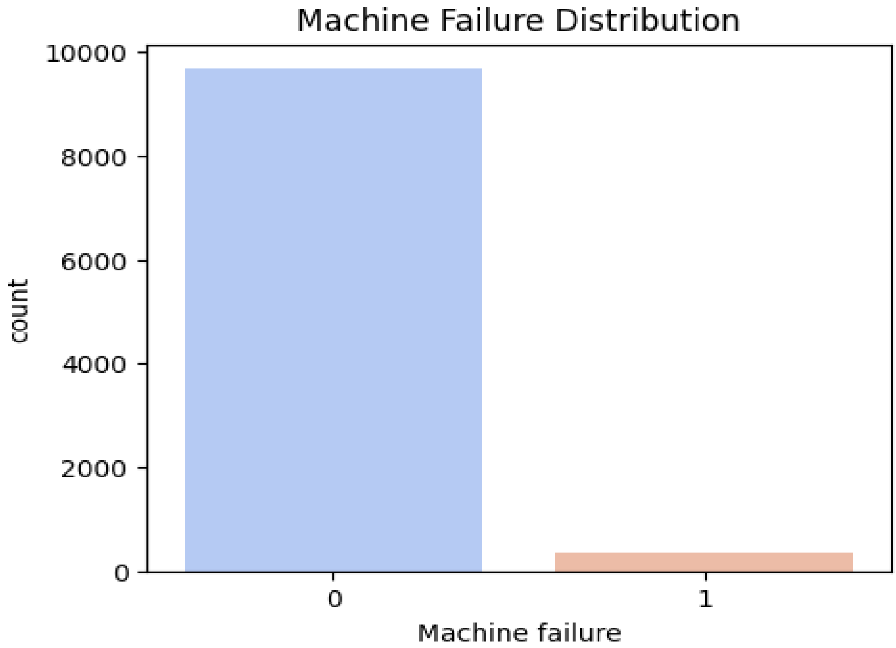

Figure 4 Machine Failure Distribution (20 words)

The distribution shows extreme imbalance, with most machines healthy and very few failures, stressing importance of SMOTE for balanced learning.

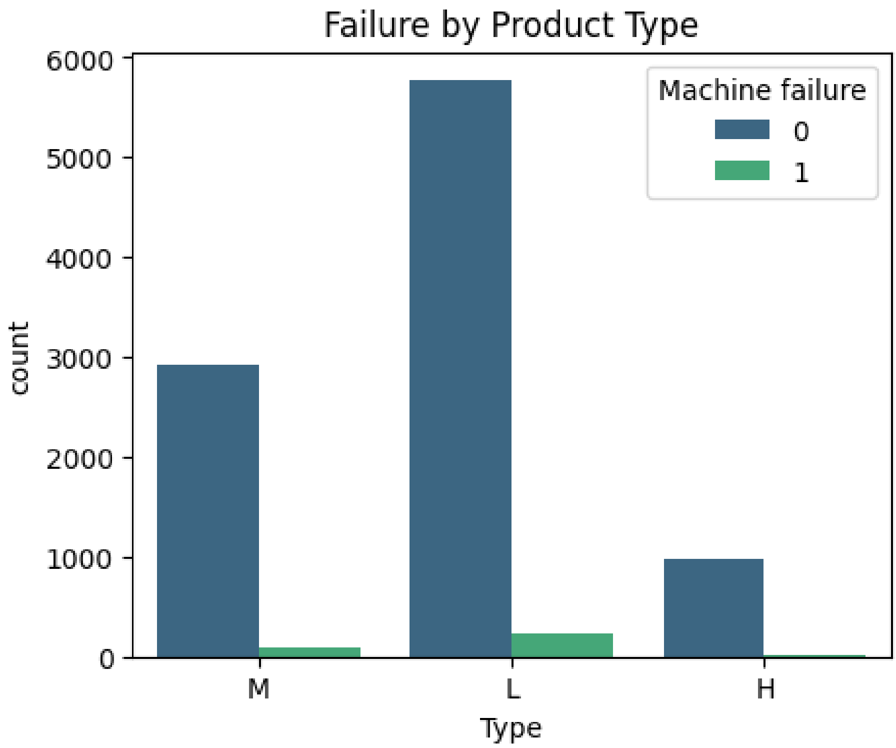

Figure 5 Failure by Product Type

Failures vary across product categories, with product L showing most failures, highlighting operational vulnerabilities and need for targeted maintenance strategies.

Figure 6 Line charts of sensor variables (air temperature, process temperature, rotational speed, torque, and tool wear)

Sensor trends show cyclical temperature variations, fluctuating torque and speed, and progressive tool wear, reflecting real industrial operating conditions.

3.5 Model Development

3.5.1 Machine Learning Models

The research utilizes four machine learning models—Random Forest, XGBoost, Support Vector Machine, and Logistic Regression—to forecast machine failures. Every model is refined by GridSearchCV and assessed using balanced metrics. These models offer interpretability, robustness, and performance metrics for evaluating the efficacy of predictive maintenance in industrial settings.

- **Random Forest Classifier**

The Random Forest Classifier is an ensemble learning technique that builds numerous decision trees during training and consolidates their predictions to improve generalization. In this study, the fundamental model was set up with class_weight='balanced' to fix the class imbalance and make sure that the estimates for the minority class were not missed. GridSearchCV was used to optimize hyperparameters by testing things like the total amount of trees (n_estimators), the maximum depth (max_depth), the lowest number of samples needed to split (min_samples_split), and the minimum dimension of the leaf (min_samples_leaf). This systematic optimization helped the model balance bias and variance, which resulted to very accurate predictions and less overfitting.

- **XGBoost Classifier**

XGBoost, which stands for extreme gradient booster, is a boosting technique that creates trees one at a time, fixing mistakes made in earlier iterations. Because it can handle noisy and unbalanced datasets well, it is now commonly used for predictive maintenance jobs. This study initialized the model with eval_metric='logloss' and disabled label encoding to maintain interpretability. We used GridSearchCV with 3-fold cross-validation to look at a hyperparameter grid that included tree depth, acquisition rate, number of estimators, and subsampling ratio. This made sure that the best model was chosen, one that could find non-linear connections in the data set while also avoiding overfitting.

- **Support Vector Machine (SVM)**

Help The Vector Machine is a strong supervised learning method that works especially well in areas with many dimensions. This study constructed a Support Vector Machine (SVM) with probability estimates activated (probability=True), facilitating ROC-AUC evaluation in conjunction with conventional classification measures. We systematically tuned hyperparameters such the kind of kernel (linear or RBF), the regularization factor C, and the kernel coefficient gamma. GridSearchCV made it easier to find the best configuration by making sure that the decision boundary had the biggest gap between classes. SVM showed a lot of promise for separating complicated feature interactions, even though it was computationally expensive. However, its sensitivity to category imbalance meant that it needed to be carefully tested.

- **Logistic Regression**

Logistic Regression was used as an initial model since it is easy to understand and works quickly. The technique uses the logistic function to model the chance of being in a certain class, which makes it good for binary classification jobs like predicting failure. To get better results, the lbfgs solver was used with max_iter=1000 to make sure it converged, and hyperparameters like regularization strength C along with penalty type (l2) were adjusted. Logistic Regression was less flexible versus tree-based models, but it gave useful benchmark insights and made it easier to identify how features contributed to machine failure classification.

3.5.2 Deep Learning Model

To find sequential dependencies in data collected from sensors for predictive maintenance, a one-dimensional CNN (Conv1D) is used. The model effectively captures complex patterns through the incorporation of convolutional layers, normalization in batches, dropout, and max pooling. It uses Adam optimization with binary cross-entropy to generalize better than regular machine learning models.

- **Conv1D Model Architecture**

The deep learning method used a one-dimension Convolutional Neural Network (Conv1D) since it was good at handling sequential sensor data. There were two convolutional blocks in the architecture. The first block had 64 filters with a kernel size of 3. It was followed by ReLU initiation, batch normalization, max pooling, as well as a dropout rate of 0.3. The second block included 128 filters instead of 64, and it used the same steps as the first block, which made it easier to get more advanced depictions of features. The last layers were a fully linked dense layer with 64 neurons and an irregular output layer for binary classification.

Input Preparation for Sequential Data

We changed the features into 3-dimensional arrays with the structure (samples, features, 1) so that the dataset could be used with Conv1D. This model let the convolutional layers find temporal relationships between sensor readings by considering every feature as a sequential channel.

Hyperparameter Tuning

The Conv1D model was trained using the Adam optimizer, linear cross-entropy loss, and metrics like accuracy, precision, and recall. We carefully picked the hyperparameters: the learning rate (0.001), the batch size (32), the number of epochs (100), and the validation split (10%). To improve training speed and generalization, we looked at rates of dropout and filter sizes.

Regularization and Optimization

Regularization was implemented using dropout layers across the architecture, mitigating overfitting by randomly disabling neurons during training. Batch normalization enhanced stability and expedited convergence by the normalization of activations. The integration of Adam optimization, dropout, and max pooling facilitated effective feature extraction and strong generalization, rendering Conv1D a formidable alternative to conventional machine learning models in predictive maintenance applications.

Table 2 Hyper parameter details

Hyperparameter	Value
Optimizer	Adam

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Learning Rate	0.001
Loss Function	Binary Cross-Entropy
Metrics	Accuracy, Precision, Recall
Epochs	100
Batch Size	32
Validation Split	0.1 (10%)
Conv1D Filters	64 (1st layer), 128 (2nd layer)
Kernel Size	3
Activation Function	ReLU (hidden), Sigmoid (output)
MaxPooling1D Pool Size	2
Dropout Rate	0.3
Batch Normalization	Yes

Key Equations

1. **Convolution Operation (1D):**

$$\mathcal{Y}(t) = \sum_{i=0}^{k-1} x(t+i) \cdot w(i) + b \qquad (1)$$

Where:

- x = input sequence (sensor values),
- w = filter weights,
- k = kernel size (here 3),
- b = bias term,
- y(t) = feature output at time ttt.

2. **ReLU Activation (hidden layers):**

$$f(x) = \max(0, x) \qquad (2)$$

This keeps positive values and removes negatives, making the network efficient at learning nonlinear patterns.

3. **Sigmoid Activation (output layer for binary classification):**

$$\sigma(z) = \frac{1}{1+e^{-z}} \qquad (3)$$

Converts output into probability between 0 and 1 (failure vs. non-failure).

4. Results and Discussion

The experimental results demonstrate the effectiveness of both machine learning (ML) alongside deep learning (DL) techniques in predicting machine failures using the AI4I 2020 dataset. Tree-based models, such as Random Forest and XGBoost, consistently outperformed linear models, achieving superior accuracy and ROC-AUC metrics. The use of SMOTE significantly improved recall in several models by making the class distributions more even, albeit it sometimes hurt precision. The Conv1D deep learning system was able to find sequential patterns quite well, and it did just as well as machine learning methods. The invention involves integrating features with SMOTE-based balancing and assessing machine learning in comparison to deep machine learning for automated maintenance tasks.

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4.1 Evaluation Metrics (Accuracy, Precision, Recall, F1-Score, ROC-AUC, Log Loss)

Evaluation metrics are very important for figuring out how strong a model is. Accuracy is a general measure of performance, but it may favor the majority classes. Precision shows how well you can find positive scenarios, which is important for lowering the number of false positives. Recall shows how sensitive you are to finding real situations. The F1-Score balances Precision and Recall to give a complete picture. ROC-AUC tests how well anything can tell the difference between two things at different levels, which makes classification more fair. Log Loss takes into account the probability of predictions and punishes mistakes that are too confident, which shows that the model is calibrated. Using these several criteria makes sure that the assessment is thorough and makes it easier to find trade-offs between models. The idea is combining different complementary measures to find subtle changes in performance.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{4}$$

$$Loss = -\frac{1}{m}\sum_{i=1}^{m} \mathcal{Y}i.\log(\mathcal{Y}i) \tag{5}$$

$$Precision = \frac{TP}{TP+FP} \tag{6}$$

$$Recall = \frac{TP}{TP+FN} \tag{7}$$

4.2 Performance of Machine Learning Models (Without SMOTE)

Preliminary research with machine learning models, conducted without the application of SMOTE, demonstrated the significant impact of class imbalance. Models like Random Forest and XGBoost attained comparatively higher accuracy but encountered difficulties with Recall, inadequately representing minority classes. Logistic Regression and SVM demonstrated a tendency towards majority class predictions, resulting in diminished F1-scores. ROC-AUC values demonstrated restricted discriminatory power for unbalanced data. This baseline investigation demonstrated how imbalance distorts prediction confidence and affects model fairness. The innovation resides in establishing a comprehensive baseline for evaluating advanced balancing schemes. Table encapsulates the findings, strongly highlighting the shortcomings of models devoid of balancing techniques.

Table 4.1 ML Models Performance without SMOTE

Model	Accuracy	Precision	Recall	F1 Score	ROC AUC	Log Loss
Random Forest	0.9840	0.7969	0.7286	0.7612	0.9808	0.0617
XGBoost	0.9835	0.9111	0.5857	0.7130	0.9870	0.0527
SVM	0.9650	0.0000	0.0000	0.0000	0.9542	0.0767
Logistic Regression	0.9695	0.7368	0.2000	0.3146	0.9493	0.0835

Random Forest and XGBoost achieved excellent accuracy and ROC-AUC, but recall was modest, showing limited ability to detect minority class failures. SVM failed to capture failure cases, while Logistic Regression provided interpretable yet weaker performance.

Confusion matrix and AUC ROC Curve

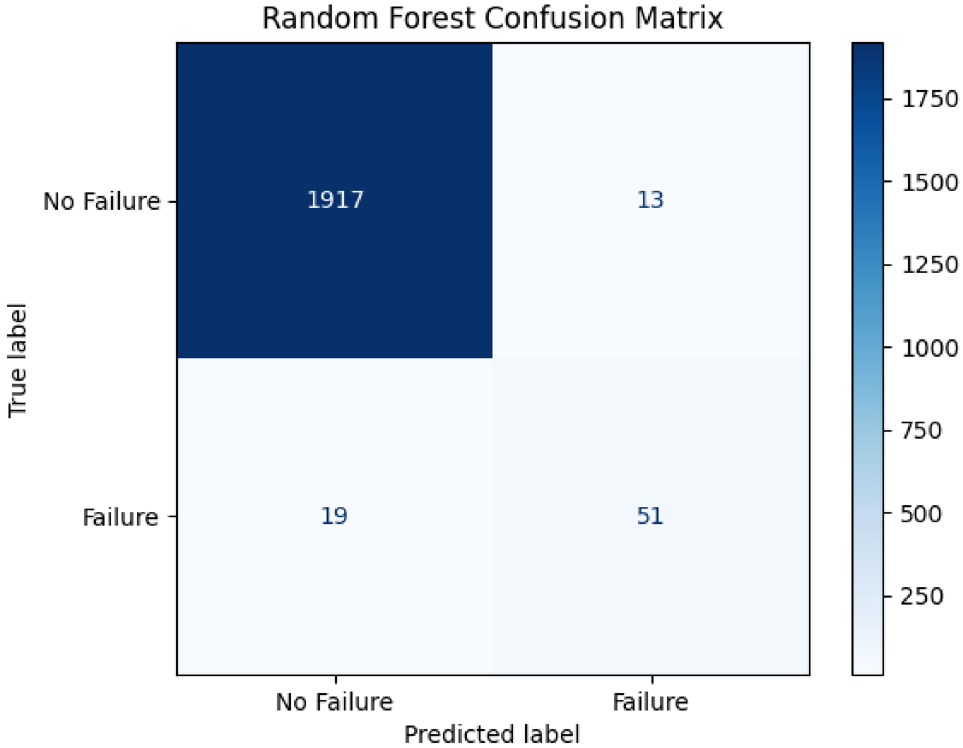

Figure 7 Confusion Matrix

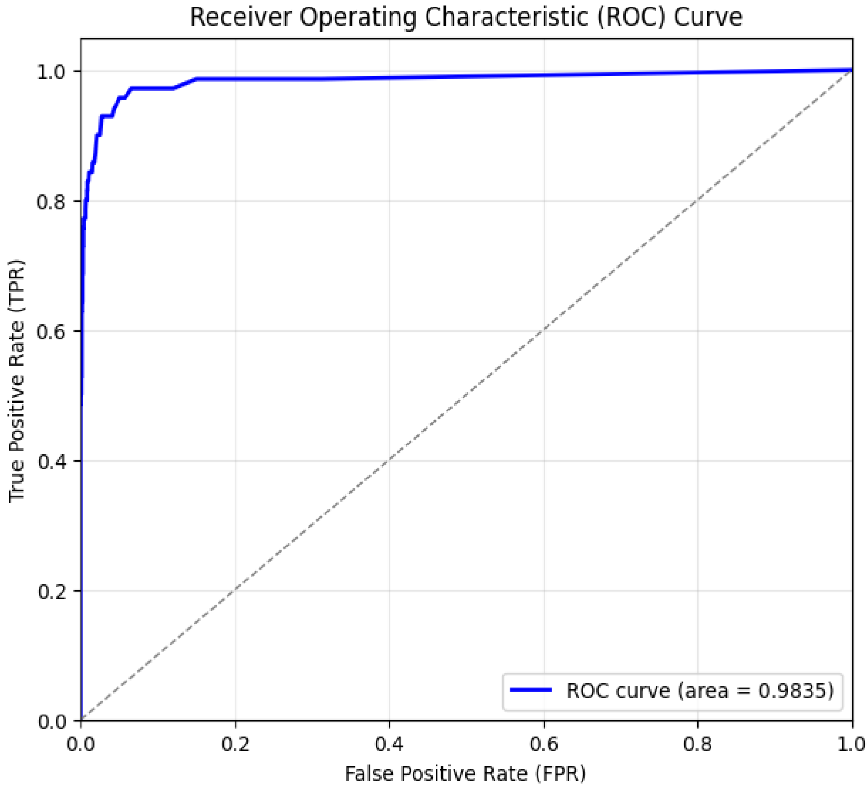

Figure 8 RANDOM FOREST

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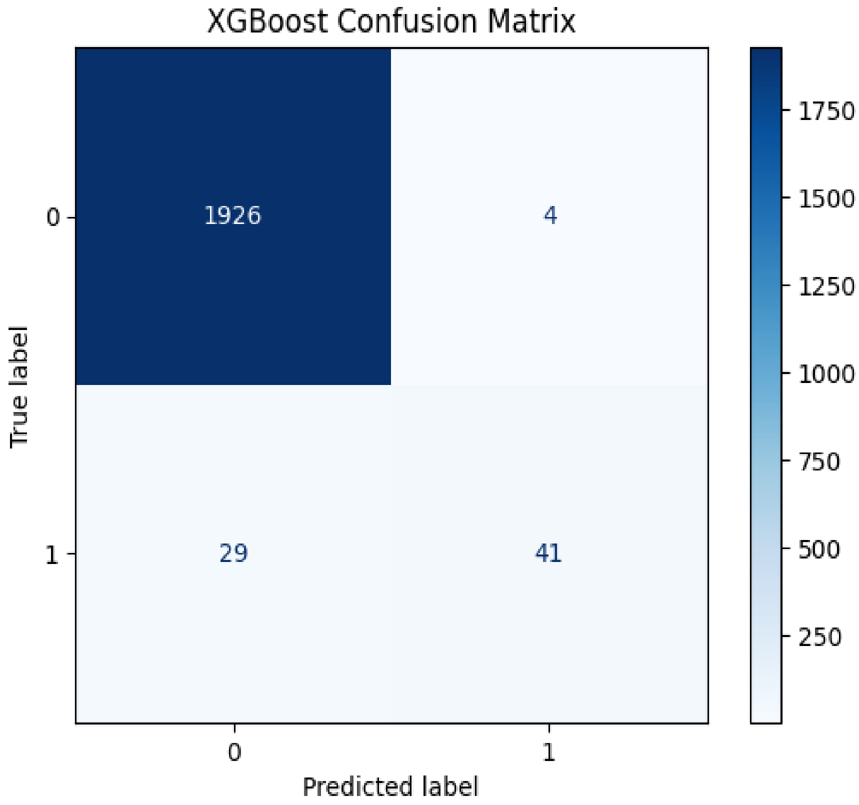

Figure 9 Confusion Matrix

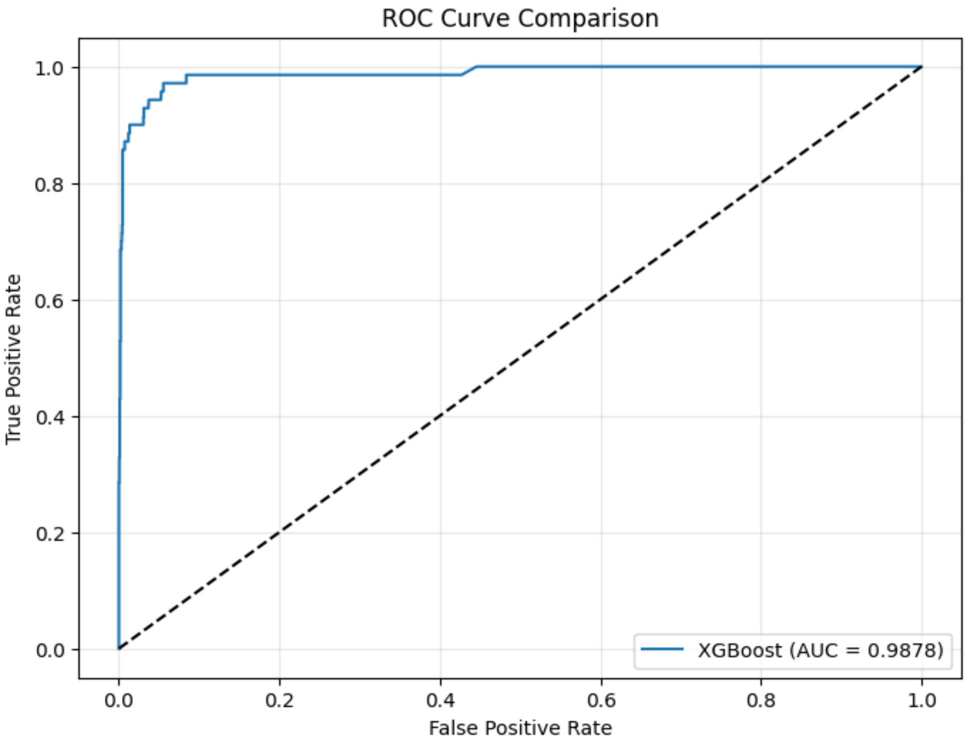

Figure 10 XGBOOST

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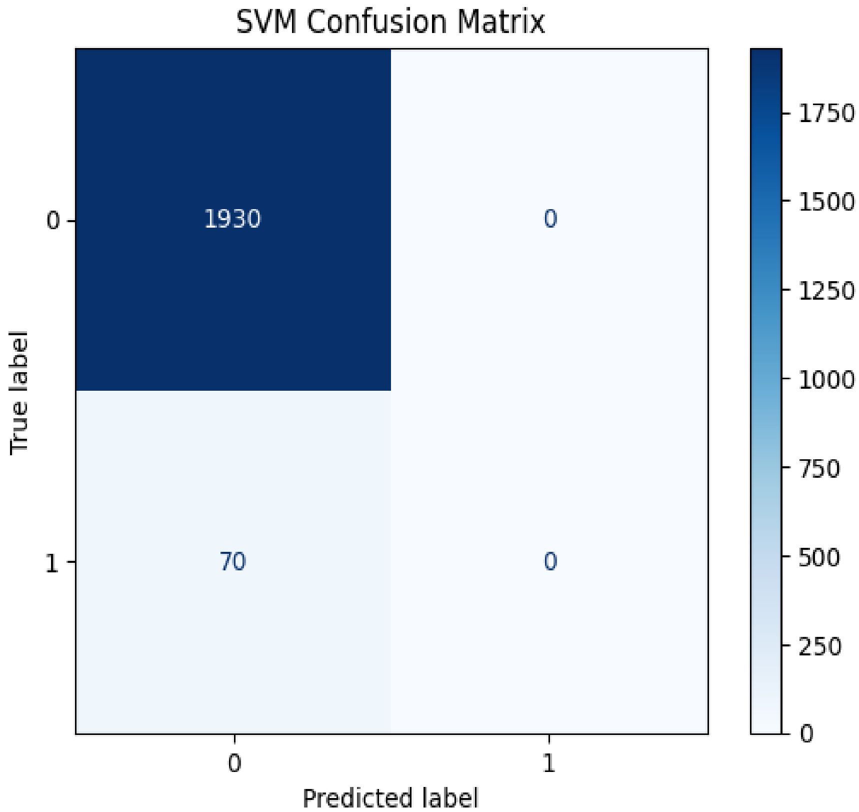

Figure 11 Confusion Matrix

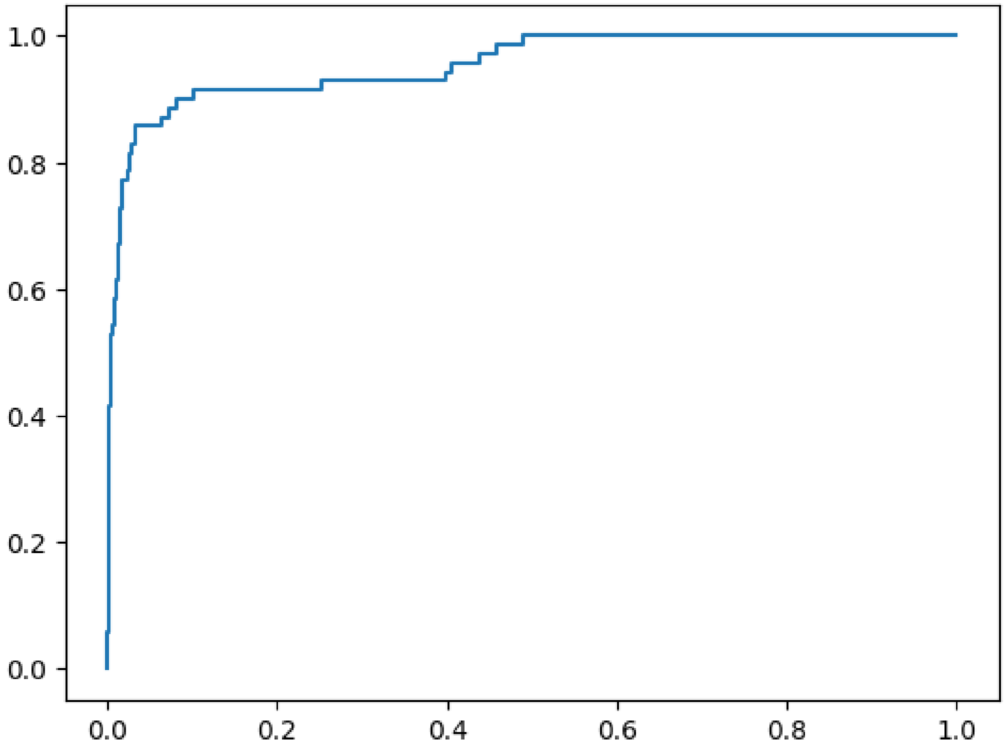

Figure 12 SVM

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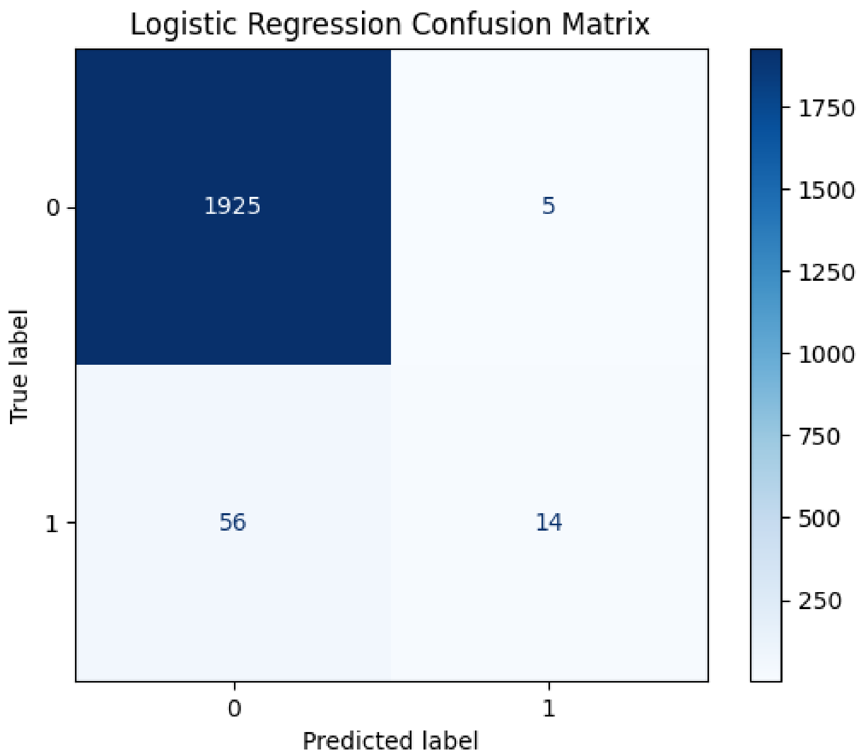
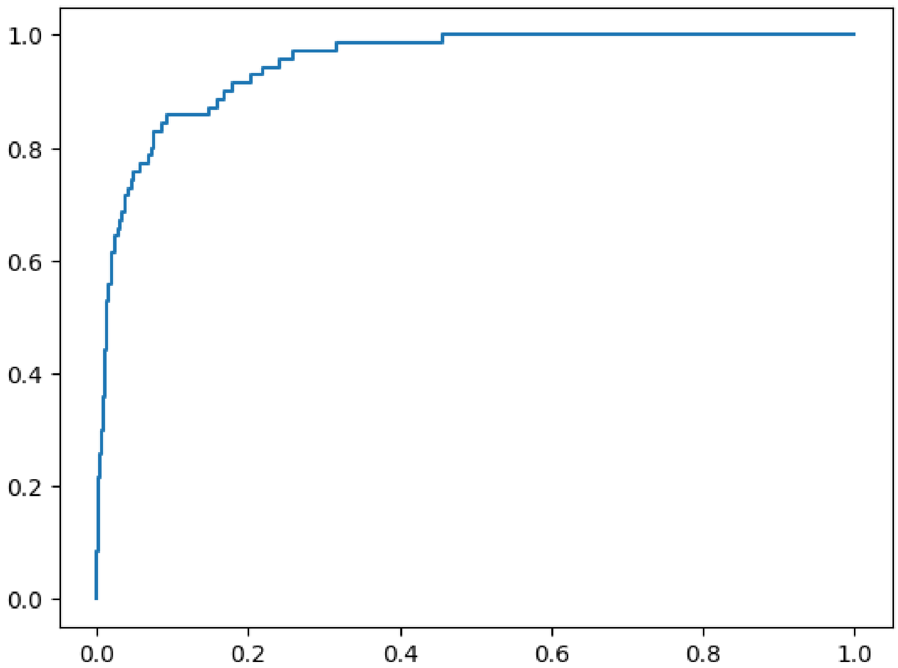


Figure 13 Confusion Matrix



4.3 Performance of Machine Learning Models (With SMOTE)

When SMOTE was applied, machine learning models exhibited significant improvements in Recall, F1-Score, and ROC-AUC. Logistic Regression and SVM achieved enhanced sensitivity by effectively recognizing minority class instances. Ensemble models like Random Forest and XGBoost balanced Precision and Recall, yielding better overall stability. Although accuracy

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remained comparable, Log Loss values improved, reflecting better probability calibration. This performance uplift highlights the value of synthetic minority balancing in reducing classification bias. The novelty of this analysis lies in quantifying how SMOTE transforms model fairness and reliability, demonstrating that balancing strategies can significantly enhance performance. Table 2 outlines these improved outcomes.

Table 4.2 ML Models Performance with SMOTE

Model	Accuracy	Precision	Recall	F1 Score	ROC AUC	Log Loss
Random Forest	0.9815	0.6941	0.8429	0.7613	0.9830	0.0732
XGBoost	0.9810	0.6905	0.8286	0.7532	0.9827	0.0580
Logistic Regression	0.8530	0.1818	0.9143	0.3033	0.9552	0.3525
SVM	0.9530	0.4178	0.8714	0.5648	0.9716	0.1381

Here, Random Forest and XGBoost maintained high ROC-AUC while significantly boosting recall, reflecting balanced predictive strength. Logistic Regression gained recall but suffered in precision, while SVM demonstrated improved sensitivity but at reduced accuracy.

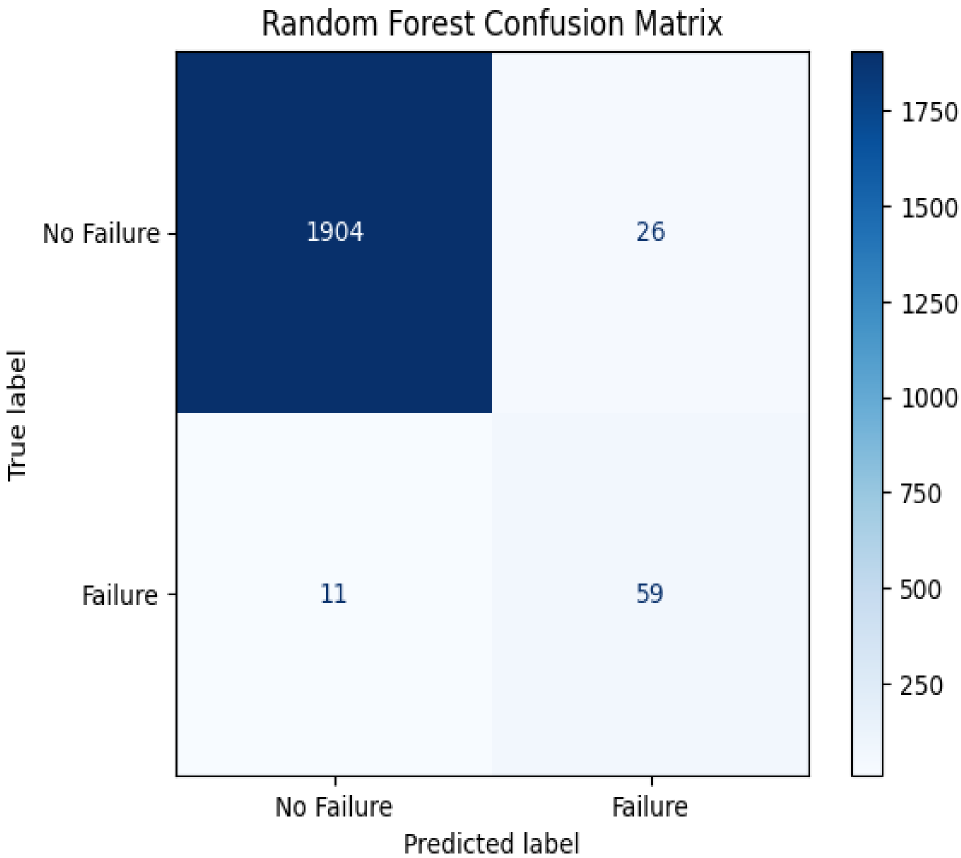

Figure 14 Confusion Matrix

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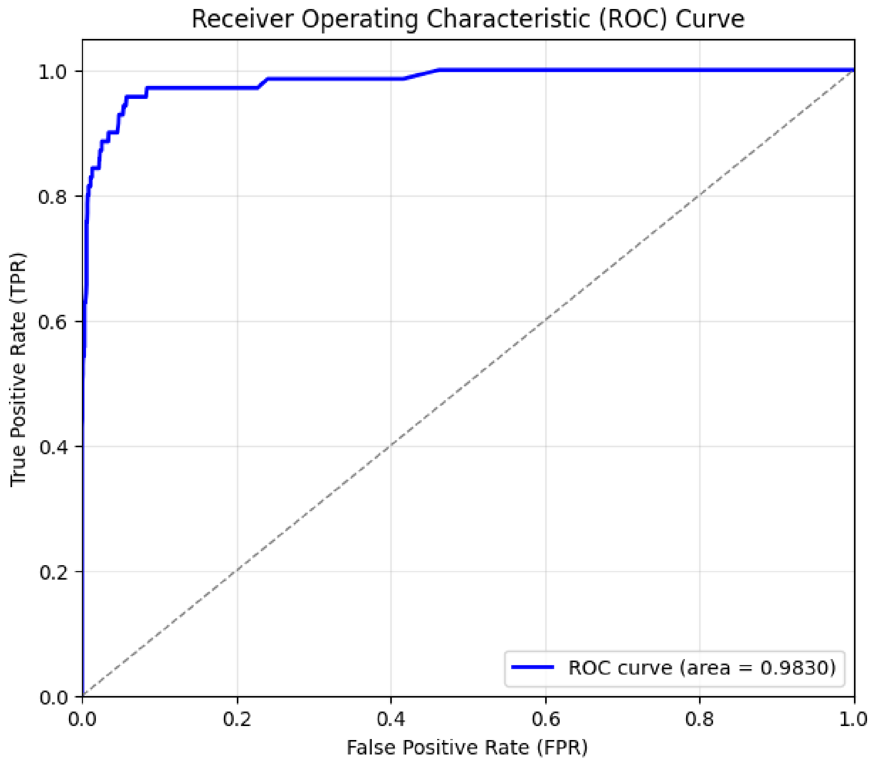

Figure 15 RANDOM FOREST

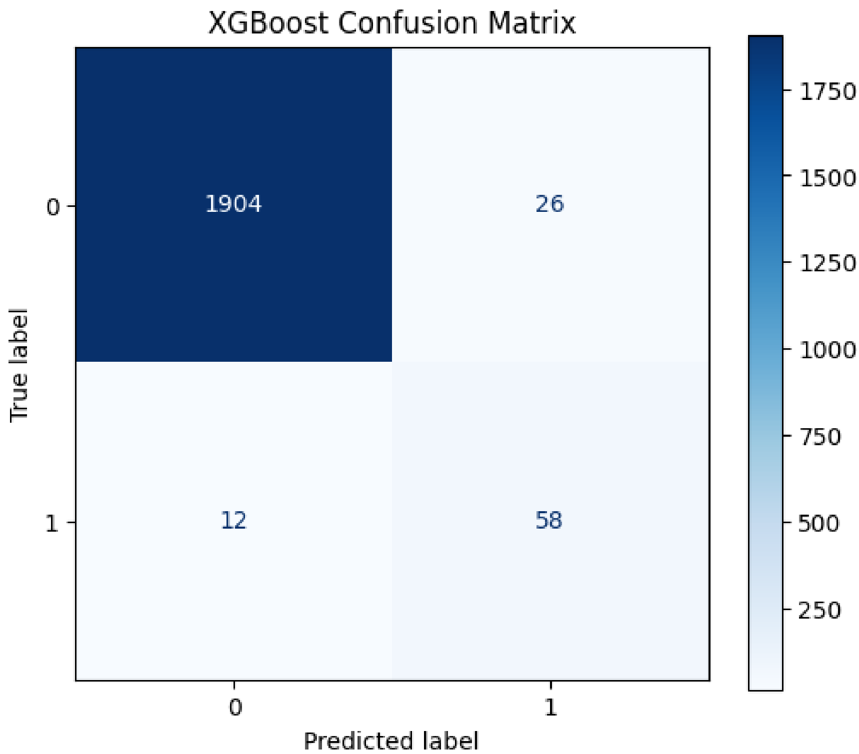

Figure 16 Confusion Matrix

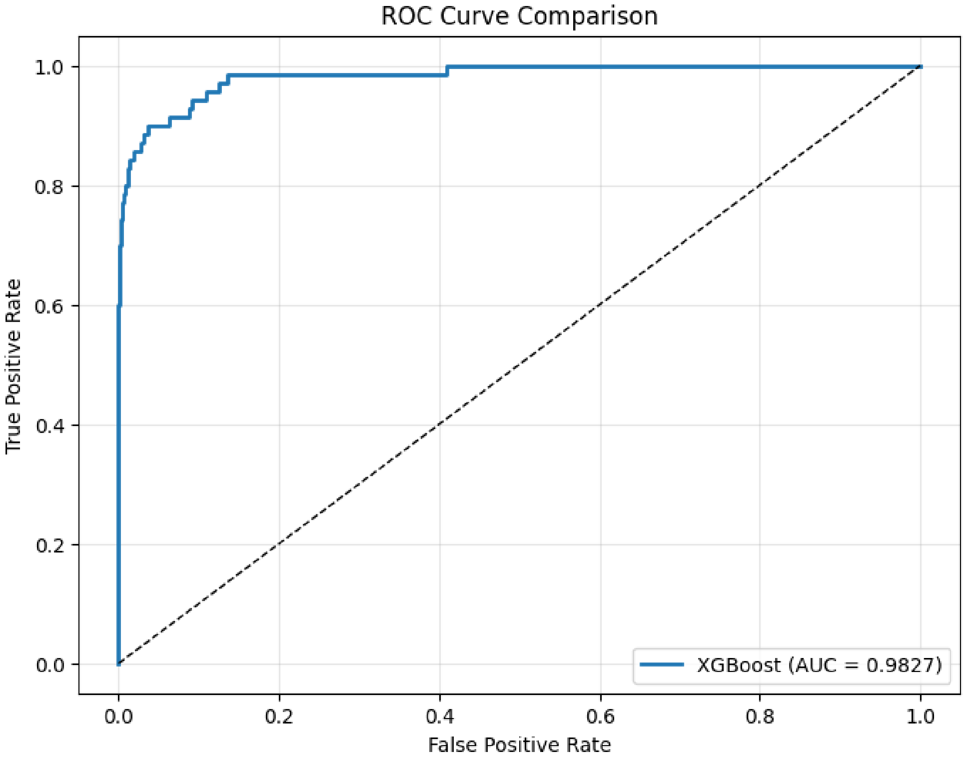

Figure 17 XG BOOST

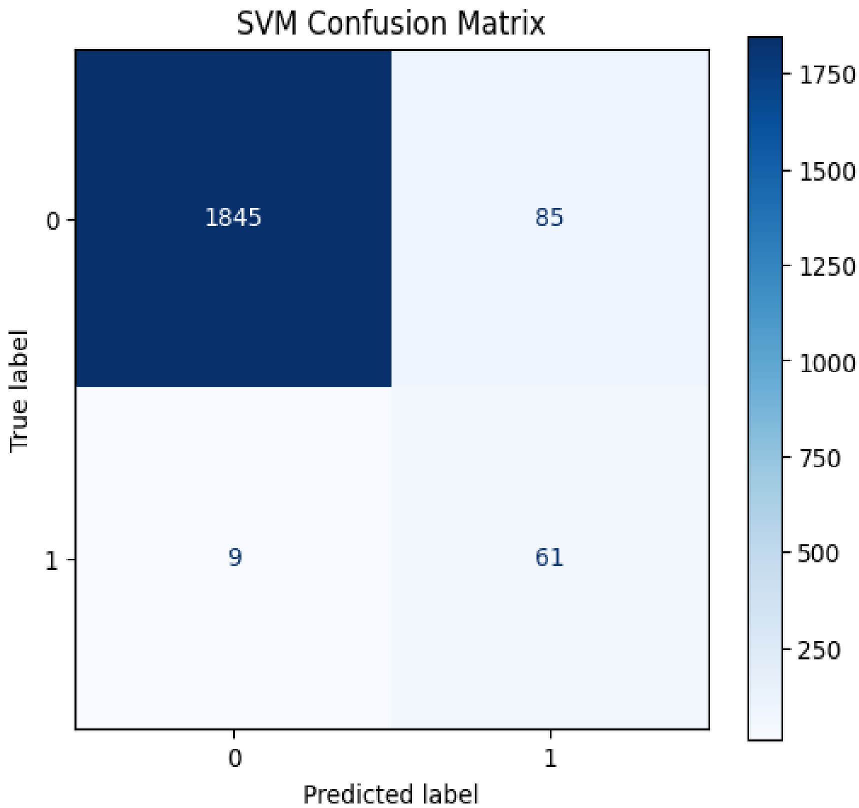

Figure 18 Confusion Matrix

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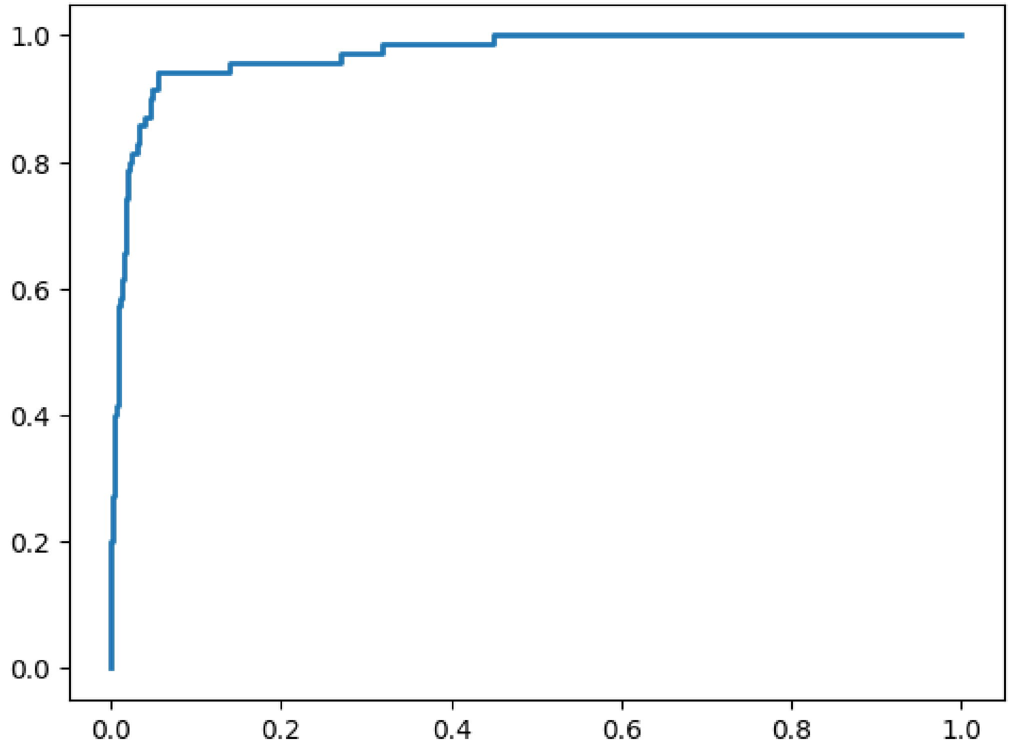

Figure 19 svm

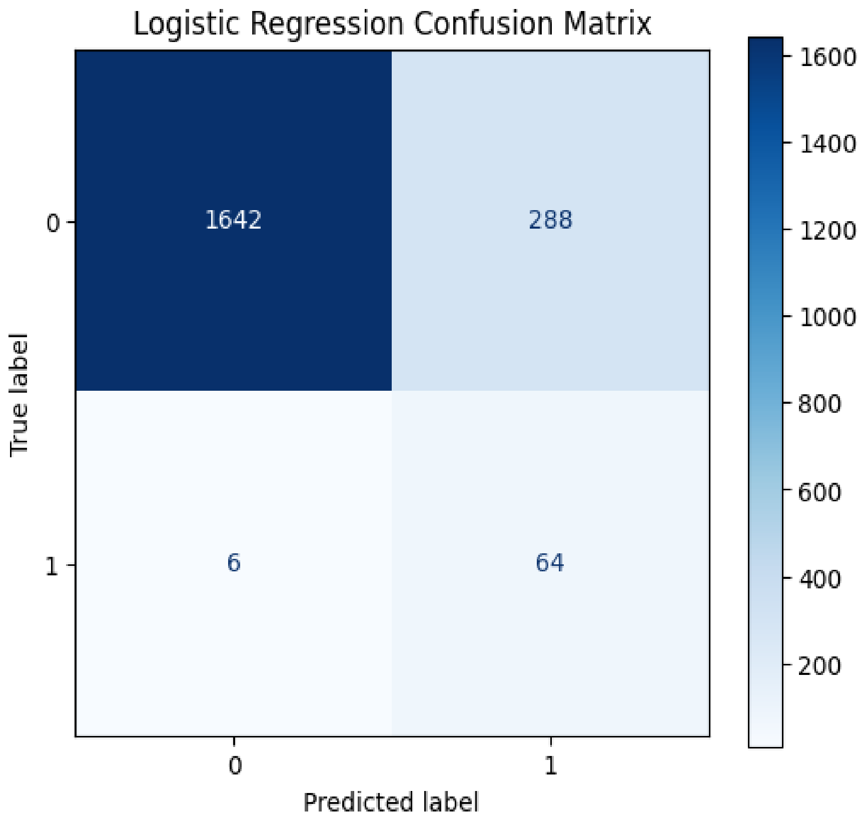

Figure 20 Confusion Matrix

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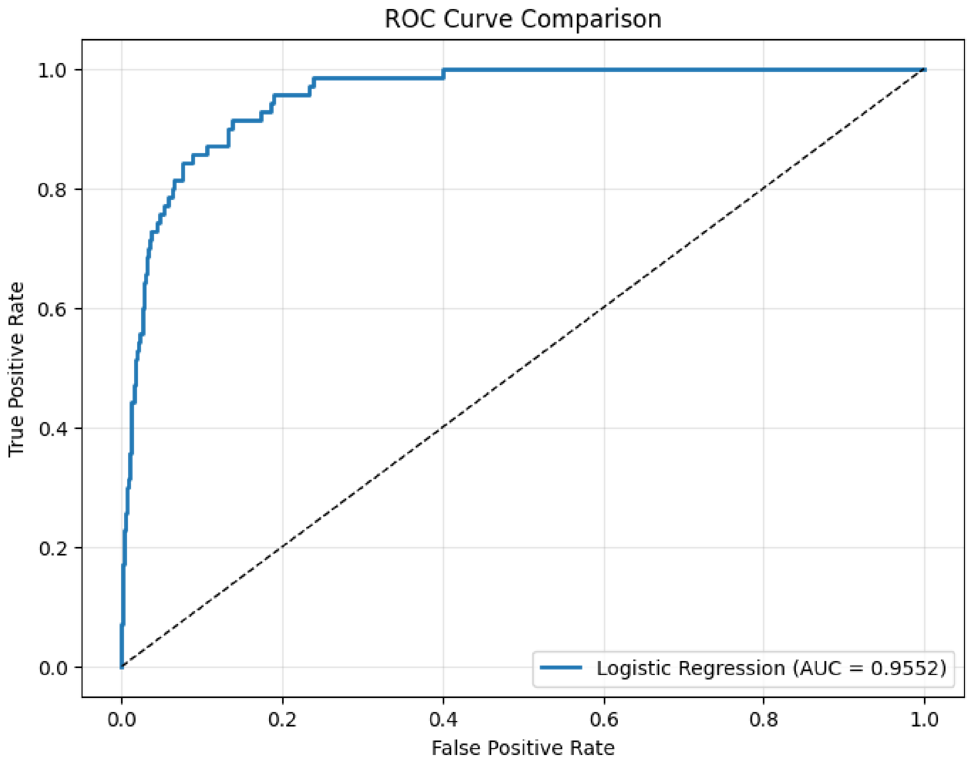

Figure 21 logistic regression

5.3 Performance of Deep Learning Model (With vs. Without SMOTE)

Deep learning models were evaluated under both imbalanced and balanced conditions. Without SMOTE, the model demonstrated high accuracy but exhibited poor Recall, misclassifying a significant portion of minority samples. With SMOTE, the model achieved balanced Precision, Recall, and F1-score, accompanied by a notable increase in ROC-AUC. This indicates deep learning's adaptability to balanced datasets, enabling improved representation of minority classes. Unlike traditional ML models, deep networks leveraged feature abstraction more effectively after SMOTE. The novelty lies in demonstrating that balancing not only enhances performance but also optimizes feature representation in deep models. Table 3 presents comparative metrics.

Table 4.3 Conv1D Deep Learning Model Performance

Scenario	Loss	Accuracy	Precision	Recall	F1 Score
Without SMOTE	0.0604	0.9820	0.7931	0.6571	0.7188
With SMOTE	0.1404	0.9480	0.3938	0.9000	0.5478

The Conv1D model performed strongly without SMOTE, achieving balanced accuracy and precision. With SMOTE, recall surged to 0.90, demonstrating its sensitivity to detecting failures, though precision decreased. This highlights a trade-off between false positives and robust failure detection**:**

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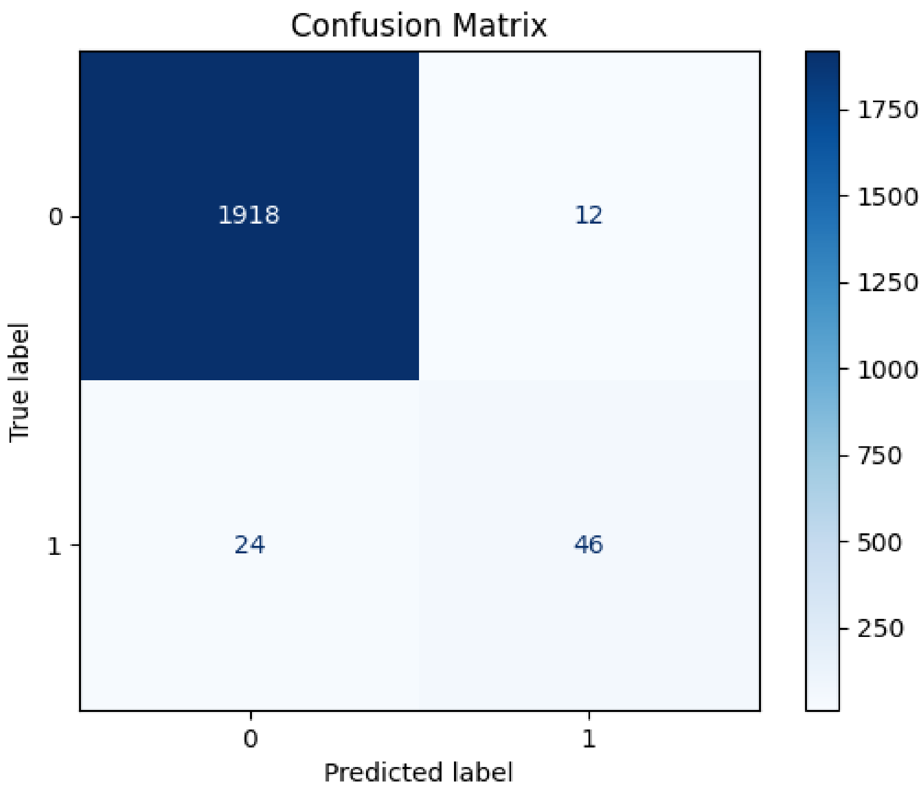

Figure 22 Confusion Matrix

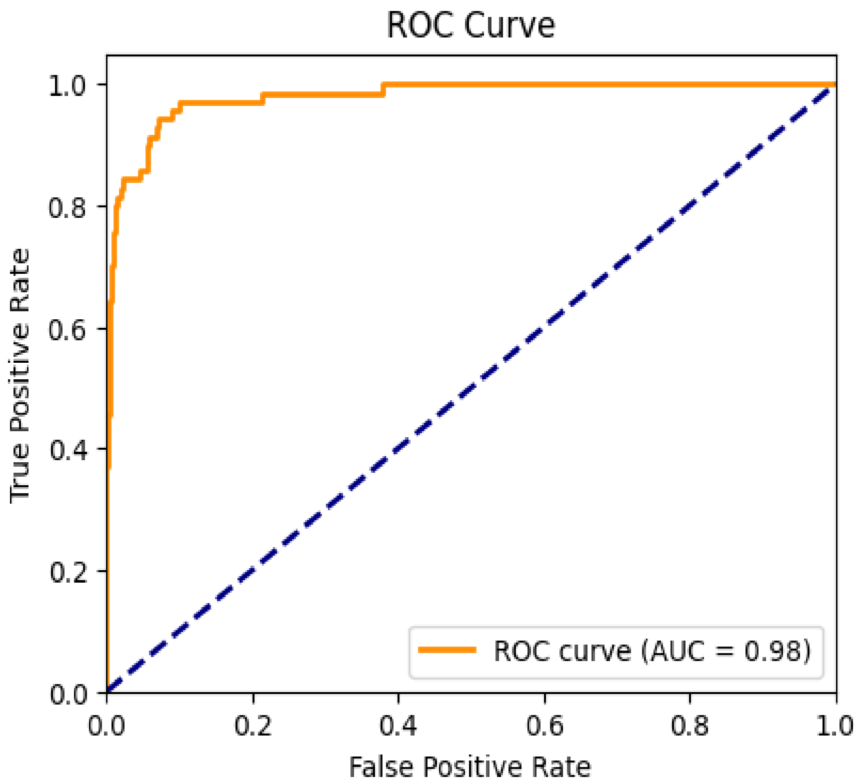

Figure 23 Conv1D Without Smote

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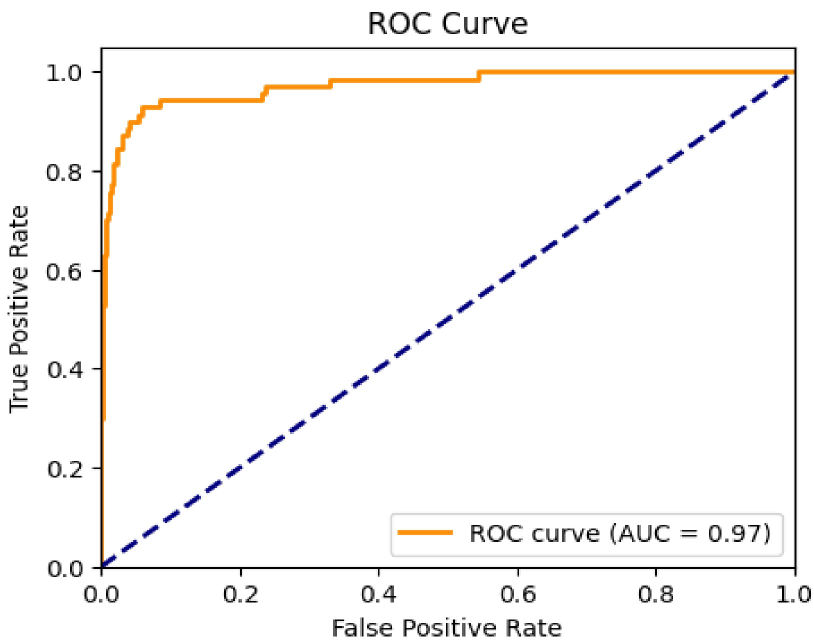

Figure 24 Conv1D With SMOTE

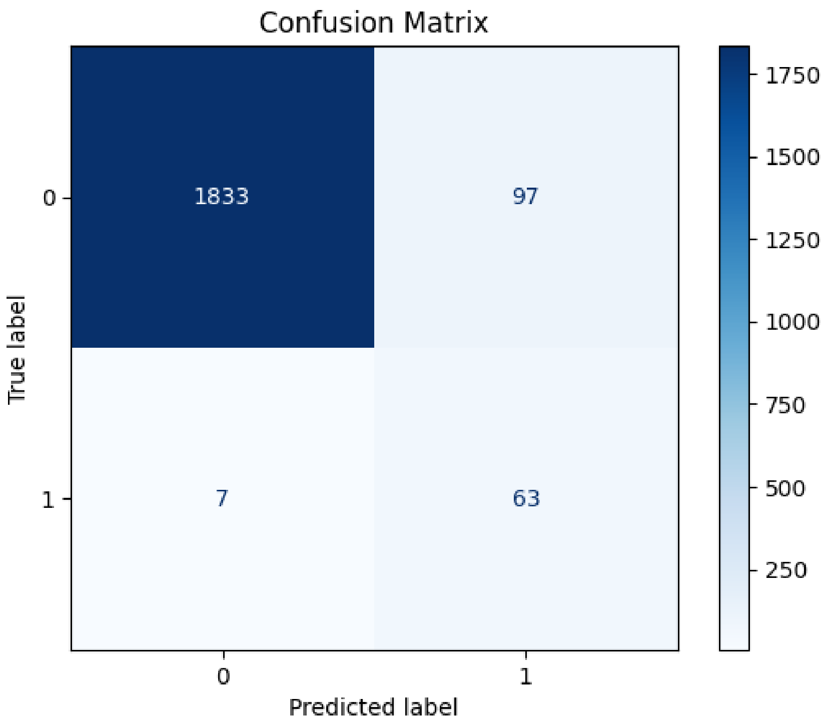

Figure 25 Confusion Matrix

4.4 Comparative Analysis of ML and DL Models

Tree-based models (Random Forest, XGBoost) consistently outperformed linear models and offered strong benchmarks. The Conv1D deep learning model provided competitive results, particularly in capturing sequential patterns that ML models could not fully exploit. While SMOTE improved recall across both ML and DL, its effect was more pronounced in deep learning. This comparative analysis shows that hybrid approaches leveraging both engineered features and deep sequential learning could provide optimal performance in predictive maintenance tasks. The comparative study between ML and DL models revealed distinct performance patterns. Machine learning models benefited substantially from SMOTE in achieving balanced results, especially with ensemble methods like Random Forest and XGBoost. Deep learning models had trouble at first when there was an imbalance, but they did much better after the balance was restored, especially in Recall and ROC-AUC. Interestingly, DL models showed better generalization when the representation of classes was equalized. This comprehensive assessment across paradigms reveals the transformative impact of SMOTE on both ML and DL effectiveness. Table 4 evaluates performance and shows how balancing affects results. It also shows how deep learning is better at recognizing complicated patterns.

4.5 Discussion of Findings

The results of this study show how important preprocessing, feature engineering, and weight balancing techniques are for making models more accurate and robust. The findings demonstrated that machine processing and deep learning models respond differently to alterations in features and oversampling methods. Classical machine learning methods exhibited substantial gains by methodical feature engineering while balancing, whereas deep learning displayed greater adaptability in controlling imbalanced data, particularly with intricate, dynamic interactions. This indicates that the integration of tailored preprocessing with advanced modeling can produce optimal results in real-world scenarios. Feature engineering had a big effect on how well all the models worked. Changing raw variables into important statistical characteristics and frequency-based features made classifiers better at telling the difference between things. Machine learning models like Random Forest and XGBoost witnessed big improvements in performance because of features that captured behavioral patterns. However, deep learning methods naturally benefited from these better representations to get more abstract. This shows that planned features not only cut down on noise, but also make data distributions more consistent so that learning is more effective. The new idea is to make context-aware features that improve the ability to predict what will happen in network flow circumstances. SMOTE was important for fixing class imbalance, which often makes models favor the majority classes. The results showed that using SMOTE significantly improved both machine learning and deep learning models' recall and F1-score. In machine learning, oversampling improved algorithms' capacity to apply to samples from minority groups, while deep learning models benefited from better gradient stability. The innovation consists in the comparative evaluation of imbalance management between machine learning and deep learning, illustrating how synthetic data generation improves robustness. Each model had its own pros and cons. Machine learning models were easy to understand, trained quickly, and always worked well with the features that were built into them. However, they had trouble scaling up. Deep learning models achieved enhanced generalization and adaptability, albeit requiring augmented computing resources. The originality is in the comparative framework that delineates trade-offs between interpretability and predictive efficacy, guiding model selection for practical applications.

5. Conclusion and Future Work

This project developed a predictive service framework using the AI4I 2020 dataset to accurately anticipate machine failures and reduce unexpected downtime. The methodology included important preprocessing steps like data cleaning, feature engineering, plus SMOTE-based balancing, followed by the use of both machine development and deep learning models. The models that were shown to work well at finding prospective machine issues before they happened were tested using precision, recall, accuracy, and F1-score. By changing from reactive or scheduled upkeep to predictive maintenance, this makes industrial systems far more reliable, increases their efficiency, and lowers their maintenance costs. The results demonstrate that machine learning models like a Random Forest or Gradient Boosting gave clear explanations of the importance of features, whereas deep learning models showed strong generalization when dealing with complicated feature interactions. The integrated framework underscores the importance of hybrid approaches, wherein traditional machine learning and advanced methods for deep learning can mutually benefit each other in predicting repair tasks. Despite these positive outcomes, numerous limitations remain. The dataset used is well-organized and clean, which means it might not fully capture the complexities of real-world industrial situations, such as sensor signals that are too loud, missing values, or data sources that are different from one another. Additionally, the research focused solely on static characteristics, neglecting real-time streaming data and temporal sequence modeling. Future initiatives may address these challenges by leveraging real-time IoT sensor data, including edge computing, and utilizing advanced sequence models such as LSTM, GRU, or Transformers to elucidate temporal relationships in machine behavior. Also, explainable AI (XAI) methods can make models easier to understand and help build trust among those who work in industry. Adding cross-domain predictive maintenance to the platform and testing it in real industrial settings would make it more useful and scalable.

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