Enhancing Manufacturing Efficiency: Predictive Maintenance Models Utilizing IoT Sensor Data

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Abstract- *The IoT is now widely used, and IoT devices are prevalent in many different industries. To guarantee that machinery and processes run at peak efficiency, Industrial IIoT uses IoT sensors and gadgets to keep tabs on their surroundings. A strategy for IIoT that is gaining popularity right now is predictive maintenance (PM), which tracks the condition of machines to estimate the likelihood of component breakdown. In order to accomplish PdM that works, ML algorithms must gather, process, and finally analyse vast volumes of data. This research presents a predictive maintenance framework for industrial manufacturing using IoT sensor data. This research suggests using IoT devices and ML algorithms to offer predictive maintenance. A variety of ML methods, including RF, CART, ANN, and LR classification algorithms, are used in the suggested PdM process. Recall, accuracy, precision, and a confusion matrix are utilized to assess these models' performance. Based on comparison data, the ANN model performs better than the other models, with an accuracy of 98%. RF comes in second with 92%, CART with 90.18%, and LR with 82%. These findings demonstrate that the ANN model offers superior classification accuracy for predictive maintenance tasks, providing valuable insights for enhancing industrial maintenance strategies.*

Keywords- Predictive Maintenance (PdM), technology, Manufacturing, sensor data, IoT, machine learning.

I. INTRODUCTION

These days, most industries use cutting-edge technology (such 3D printing and sophisticated robots) to automate and improve the production process [1][2]. Industry 4.0 refers to the technological advancements that make this growth possible. With the use of this technology, businesses can provide consumers with innovative goods and services that are more dependable, efficient, and of better quality. Incorporating smart devices into operations allows organisations to precisely monitor their actions, which in turn allows them to restructure and enhance their business processes. Consider equipment maintenance, one of the most important business operations in the manufacturing area [3]. Predictive Maintenance is an idea that the IoT has introduced, which elevates the equipment maintenance process to a higher degree [4].

As a result, predictive maintenance technology may ultimately guarantee that industrial equipment is well-maintained and stays in excellent condition while also reducing resource loss from needless maintenance. Predictive maintenance technology now uses remote tracking systems to monitor the state of hardware and software in a facility. Nevertheless, in order to implement these cutting-edge solutions, it is crucial to have a thorough understanding of the trade-off among the benefits that technology may provide and the additional expenses needed during the technology deployment stage [5][6][7]. Enterprises will incur more expenses due to the need to acquire specialised expertise, software licensing, and equipment and instrumentation instruments. Accurately developing a PdM framework based on Industry 4.0 requires an understanding of a notion of PdM as well as an overview of the field. Investigated the IIoT concepts, existing predictive maintenance frameworks, and the difficulties encountered in creating and putting into practice an intelligent maintenance framework in order to accomplish this aim [8][9].

The use of IoT technology in manufacturing to gather usable information by applying different analytics to machine data collected by several sensors is known as the IIoT[10]. Data collected by machines typically includes a date-time component, which is essential for predictive modelling. Conventional maintenance practices, which involve fixing equipment only after an issue has arisen, have its roots in reactive tactics. However, a more proactive and economical alternative has emerged: predictive maintenance, which makes use of data analytics and ML approaches [11]. ML has developed into an effective instrument capable of implementing superior intelligent prediction algorithms. The capacity to handle large data and, as a result, efficiently uncover hidden relationships between it is a property of ML. These data may be created in dynamic contexts and may be complicated[12][13]. There is a procedure with distinct steps involved in applying ML to PdM. Through model training and more effective data gathering and utilisation, the goal is to successfully forecast maintenance needs. Regarding data collection, this procedure includes selecting and pre-processing historical data.

A. Contribution and aim of paper

The paper makes significant contributions in the area of PdM for manufacturing using IoT sensor data. Its key contributions are detailed below:

- Perform pre-processing including handling missing values, removing outliers, label encoding, and MinMax Scaler normalization to improve data quality.
- Effectively addresses class imbalance using oversampling to enhance model performance.
- Implements and compares multiple machine learning models—ANN, CART, RF, and LR—for predictive maintenance.
- Utilises confusion matrix, accuracy, precision, and recall metrics to thoroughly assess model performance.
- Provides actionable insights for improving predictive maintenance strategies in manufacturing environments.

B. Structure of paper

The remainder of the paper adheres to this format. A review of the predictive maintenance background in manufacturing is provided in Section II. The methodological details are provided in Section III. The analysis, discussion, and findings are compared in Section IV. Section V offers the study's outcomes as well as future research intentions.

II. LITERATURE REVIEW

The creation of PdM systems has drawn increasing attention from academics in recent years. Some background studies are provided below:

In, Liu et al., (2021) based on enhanced deep adversarial learning (LSTM-GAN), suggests a revolutionary PdM technique. Lastly, an intelligent manufacturing system case study using LSTM-GAN for PdM is given. Up to 99.68% is the failure forecast accuracy of LTSM-GAN. When LSTM-GAN is compared to other conventional techniques, it demonstrates both efficiency and accuracy[14].

In, Chen, Gao and Liang, (2023) present an independent LOPdM system built using the newest SPS and TinyML methodologies. RF and DNN show up to 99% precision under ultrashort data length, small data quantity, and low-sampling rate conditions. It demonstrates that up to 66.8% of energy may be saved by the SPS-based system. A combined prototype is put together and used for field testing. It has a high degree of accuracy for identifying faults[15].

This study Teoh et,al(2023) introduces the fog computing system that uses genetic algorithms (GAs) to manage resources and integrates ML for predictive maintenance. To test how GA, MinMin, MaxMin, FCFS, and RoundRobin fare in terms of time, money, and energy, the FogWorkflowsim model is used. The predictive maintenance model is constructed utilising real-time data sets and two-class logistic regression. The results show that when compared to MinMin, MaxMin, FCFS, and RoundRobin, the suggested method performs better in terms of execution time, cost, and energy consumption. In contrast to the second-best findings, our execution time is 0.48% quicker, cost is 5.43% cheaper, and energy use is 28.10% lower. The prediction model was 95.1% accurate during training and 94.5% accurate during testing[16].

In, Samatas, Moumgiakmas and Papakostas, (2021) conclusions were reached on the trends in ML-based PdM applications that connect AI and the IoT. Out of the six sectors that were featured, the production sector dominated with 54.55% of all articles. There were 10 different AI models, with 28.95% using ANNs, 18.42% using SVMs, and 14.47% using RFs as their favourites. Out of the twelve types of sensors that were considered, 60.71 percent and 46.42 percent of all sensors were temperature and vibration sensors, respectively[12].

In this study, Ayvazthe et.al (2021) Using IoT data from actual industrial systems, the system's efficacy was also evaluated. The evaluation's findings showed that the predictive maintenance system may successfully recognise warning signs of impending malfunctions and might even be able to avert certain production halts. The results of comparative analyses of ML algorithms suggested that the models of the boosting technique XGBoost and the bagging ensemble algorithm RF seemed to perform better than the individual methods in the analysis. The factory's production system now uses the top-performing ML models from this research[17].

IIoT applications include quality control and management, maintenance cost reduction, and overall industrial process improvement [10].

Table. 1 Comparative Study on Predictive Maintenance Models Utilising IoT Sensor Data

Author	Methodology	Data	Performance	Limitation/research gap
Ayvaz et al. (2021)	Comparative analysis of machine learning algorithms for predictive maintenance using Random Forest and XGBoost.	Real-world manufacturing IoT data	Random Forest and XGBoost outperformed individual algorithms; models integrated into the factory production system.	Limited focus on exploring other machine learning models or more complex deep learning methods. Real-time efficiency is not fully discussed.
Teoh et al. (2023)	Genetic Algorithm (GA)-based resource management with machine learning for predictive maintenance in fog computing.	Real-time datasets	Execution time is 0.48% faster, cost is 5.43% lower, and energy usage is 28.10% lower compared to other approaches. Prediction accuracy: 95.1% (train), 94.5% (test).	Limited exploration of advanced predictive models beyond two-class logistic regression. Impact of other cloud computing environments untested.
Liu et al.,	LSTM-GAN (to address vanishing gradient and mode collapse in GANs)	Case study in intelligent manufacturing	Fault prediction accuracy: 99.68%	Superior accuracy and efficiency, extends machine life, reduces maintenance costs and downtime.
Chen, Gao and Liang	Random Forest (RF), Deep Neural Networks (DNN), TinyML techniques	Self-powered sensor (SPS), simulated vibration environment	Precision: 99%, 66.8% energy savings (SPS-based system)	Ubiquitous AI applications with energy-efficient, high-precision PdM system
Samatas, Moumgiakmas and Papakostas	ANN (28.95%), SVM (18.42%), RF (14.47%)	Various IoT sensor applications	Production sector: 54.55% of total publications	Overview of sectors, AI models, and sensors used in PdM applications

A. Research gaps

The use of ML techniques for predictive maintenance (PdM) has come a long way, but there are still many gaps in PdM systems more efficient and effective.

- Approaches should be sufficiently broad to apply to a variety of sectors outside of manufacturing.
- PdM systems that are efficient with energy are a priority for adoption in areas with limited resources.
- New methods are needed to properly manage datasets that are small and unbalanced.
- Not enough sophisticated models to optimize maintenance plans with cost and downtime minimization in mind.
- A use of edge computing and the IoT has untapped promise for low-latency, real-time PdM.

Machine learning-based Predictive maintenance solutions that fill these gaps will be more effective, scalable, and robust.

III. SYSTEM DESIGN AND IMPLEMENTATION

An important part of this study's approach is a development and implementation of a PdM framework for use in industrial production. A research methodology entails various steps. The methodology for the research entails the collection of 944 observations and ten features of IoT sensor data for predictive maintenance in manufacturing. Data preparation includes tasks such as normalising, resolving missing values, encoding categorical variables with labels, and eliminating outliers. To avoid overfitting and lower dimensionality, feature selection is used, and to fix class imbalances, oversampling is used to balance the data. The dataset is split into two sections: the testing section and the training section. Many classification models are employed, such as ANN, CART, RF, and LR– (Logistic Regression). A confusion matrix, together with recall, accuracy, and precision, is utilized to evaluate a model's performance.

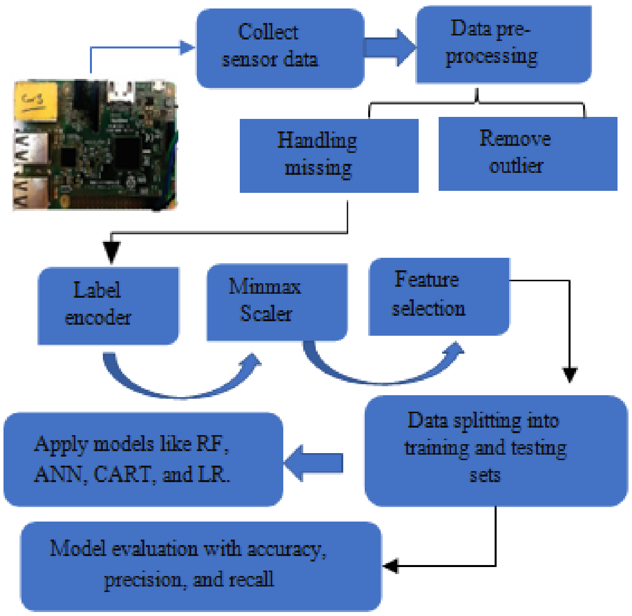

Fig. 1 Block diagram for manufacturing predictive maintenance with IoT

The following Figure 1 Block diagram for manufacturing, each step of the diagram is briefly explained below:

A. Data Collection

PdM is based on data-collecting techniques and sources. In this research, collect sensordata for predictive maintenance in manufacturing with IOT. A sample size of a dataset is 944 observations and 10 features.

B. Data Preprocessing

The term "preprocessing" refers to the steps used to make structured data more understandable and ready for use in ML models [18]. The main goal of preprocessing is to reduce the quantity of noise, redundant data, and unneeded data after enhance an input data quality. A key term of pre-processing is given in below:

- **Handle missing values:** In most cases, datasets contain missing fields or characteristics. If a tiny portion of the dataset consists of instances with missing characteristics, such instances may be eliminated.
- **Remove outliers:** Removing outliers refers to the process of identifying and eliminating data points that significantly differ by a majority of a dataset.

C. Label Encoder

A very useful tool for data preparation is the Label Encoder, which converts categorical variables into a numerical representation. In order to do this, each category in the input is given a unique number designation.

D. MinMax Scaler for normalization

The MinMaxScaler method was used in this study to rescale the features between 0 and 1. Because this method utilises statistical approaches that do not alter the variance of the data, it has the advantage of being resilient to outliers (Equation (1)).

$$x' = \frac{x - \min(x)}{\max(x) - \min(x)} \quad (1)$$

Equation (1) above illustrates that x shows an original value, x' a scaled value, max and upper limit of a feature value, and min a lower bound. Because MinMaxScaler scaling maintains a sparsity of input data, it saves time when dealing with data that has a lot of zero entries [19].

E. Feature selection

As dimensionality reduction poses a significant risk of overfitting, feature selection is an crucial part of a data preparation process. Removing unnecessary and superfluous features is how feature selection works [20].

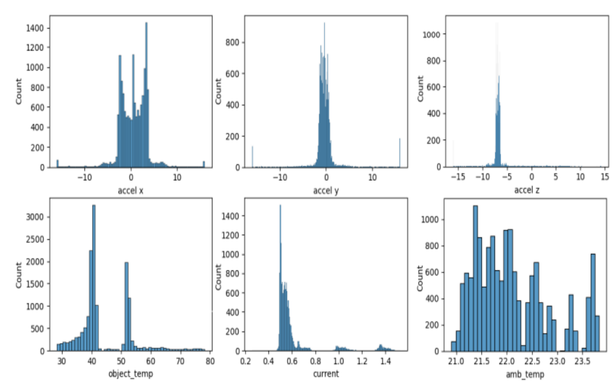

Fig. 2 Numeric features histogram

The histograms in Figure 2 shows histograms for six numeric features: ‘accel_x’, ‘accel_y’, ‘accel_z’, ‘object_temp’, ‘current’, and ‘amb_temp’, illustrating their value distributions. These plots highlight variability, central tendencies, and potential skewness, aiding in understanding the range and frequency of sensor readings and environmental conditions.

F. Data balancing with oversampling

By replicating or creating fresh representatives of the minority class, oversampling increases their numbers, thereby resolving imbalance. Undersampling, on the other hand, equalises classes by decreasing the sample size of the over-represented majority group.

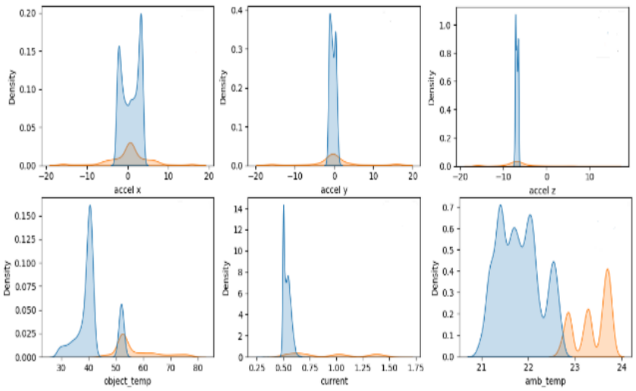

Fig. 3 Features distribution after oversampling

The distribution of various features after applying oversampling techniques is shown in Figure 3. Each graph represents a different feature, such as ‘accel x’, ‘accel y’, ‘accel z’, ‘object temp’, ‘current’, and ‘amb temp’. The blue and orange lines likely indicate the density of different classes within the dataset.

G. Data Splitting

Two sets of data are generated from the preprocessed data: one for testing and one for training. The training set comprises 80% of the entire data needed to train the model, while the testing set includes 20% of the total data required to assess its performance.

H. Classification Models

For the classification, select multiple machine and deep learning models that explained below:

1) Artificial neural network (ANN)

Typically, an ANN design will consist of three layers: hidden, output, and input. The hidden, output, and input layers make up a neural network's three primary layers. User data is received by an inputlayer, processed by a hiddenlayer, which modifies the weights for optimal efficiency. The output layer then classifies a network's output. A NN's output is conditional on the learning rule and propagation function. Equation (2) expresses the propagation function, which controls an input to a j-th neuron by an output of a previous neuron. [21].

$$parentparent\, P_j(t) = \sum_i O_j(t) x\ \omega_{ij} + b \quad (2)$$

where the previous neuron's output is represented by $Oi(t)$, the propagation function is represented by $Pj\ (t)$, the weight is represented by b, and the bias is represented by b. The learning rule adjusts the parameters of a neural network such that the network returns a useful result for a given set of inputs. When a learning rule is applied, a network's weights are adjusted in order to enhance output computation [22].

2) CART

Using a subset of the training data for which the right classification is known, the CART method finds and builds a binary decision tree. Because there are less and fewer entities in the two sub-groups created at each binary split—which correspond to the two branches that emerge from each intermediate node—a substantial training sample is necessary to achieve superior performance [23].

3) Random forest (RF)

Regression and classification challenges are addressed by the ensemble learning technique known as RF. It builds many decision trees using random samples of input data and attributes, then averages or utilises majority voting to aggregate their predictions [24]. Its capabilities include high-dimensional data handling, resistance to overfitting, and widespread use in image classification, anomaly detection, and consumer segmentation.

4) Logistic regression (LR)

Binary classification is accomplished by the use of the ML method logistic regression. Applying the sigmoid function to a linear combination of the input characteristics allows one to describe the probability that an input belongs to a specific class. By minimising the log-loss function, the training process finds the coefficients. For both numerical and categorical input characteristics, LR is an easy-to-use, effective method.

I. Evaluation metrics

Evaluation measures allow one to compute a model's performance. A suggested method was evaluated in this research using the confusion matrix, recall, accuracy, and precision. An approach to demonstrating the efficacy of a classification system is the confusion matrix. The four columns that result from comparing the expected and actual values are true negative (TN), false positive (FP), true positive (TP), and false positive (FP). False positives occur when, despite predictions to the contrary, an instance does not really have diabetes. Accuracy, recall, and precision are determined by the values in the confusion matrix.

1) Accuracy

This metric measures how well a model forecasts outcome relative to the amount of samples used as inputs. This is expressed as (3)-

$$Accuracy = \frac{TP+TN}{TP+Fp+TN+FN} \quad (3)$$

2) Precision

It is calculated by dividing the number of positive results that the classifier correctly predicted by the number of positive results that it really predicted. It may be written as 4-

$$Precision = \frac{TP}{TP+FP} \quad (4)$$

3) Recall

The ratio of valid positive findings to a total number of samples is the measure of this statistic. It may be expressed mathematically as (5)-

$$Recall = \frac{TP}{TP+FN} \quad (5)$$

The following figures shows a performance of ML models according to these performance measures for Predictive Maintenance on IoT sensor data in manufacturing area.

IV. RESULTS AND DISCUSSION

The models' experimental findings are shown in this section. Recall, precision, f1-score, and accuracy measures are utilized to assess a following result. Graphs showing an ANN model's accuracy, confusion matrix, and loss are shown in Table 2.

Table. 2 ANN model efficiency across performance matrix

Measures	**Artificial neural network**
Accuracy	98
Precision	94
Recall	95

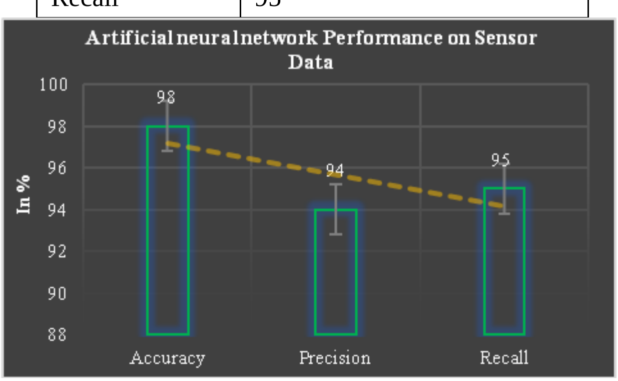

Fig. 4 Bar graph for ANN model performance

The following Figure 4 shows the ANN model performance across sensor data. In this figure, ANN has an accuracy98%, precision94%, and recall95%, demonstrating high overall performance and effective classification of positive instances.

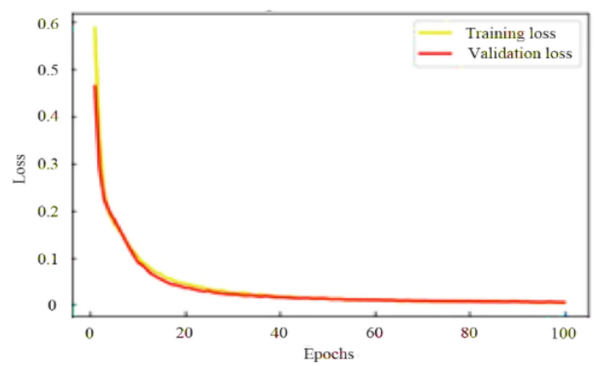

Fig. 5 Training and validation loss graph for ANN

Figure 5 above displays the training and validation loss of an ANN during a 100-epoch period. The red line indicates validation loss, while the yellow line represents training loss. Indicating that a model is learning, both begin high and progressively decline. A training loss decreases slightly faster, but both lines flatten over time, suggesting a model is improving without overfitting.

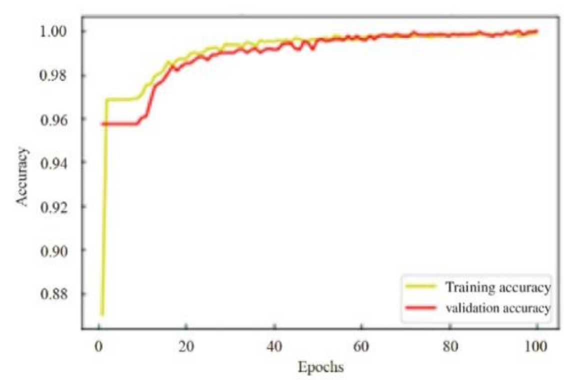

Fig. 6 Training and validation accuracy graph for ANN

Figure 6 displayed an accuracy of an ANN throughout 100 epochs of training and validation; the yellow line shows training accuracy, while a red line illustrates validation accuracy. Both lines increase as epochs progress, indicating improved performance, with training accuracy consistently higher than validation accuracy, suggesting that a model is learning effectively on both datasets.

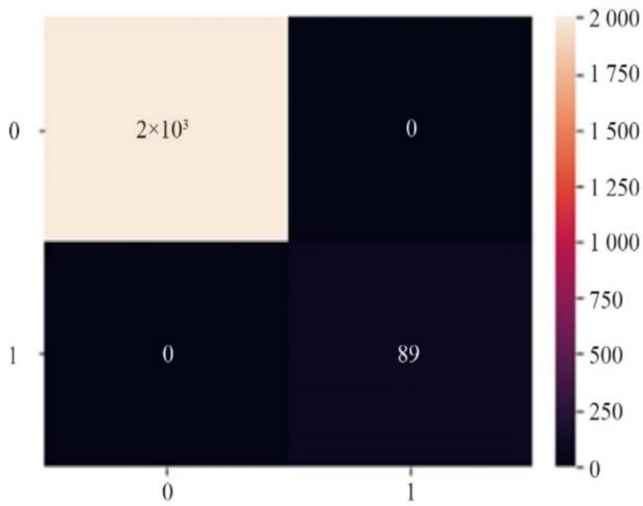

Fig. 7 Confusion matrix for ANN

An above Figure 7 displays a confusion matrix for an ANN shows excellent performance in classifying class 0, with 2000 TP and no FP or negatives. For class 1, there are 89 TP, but the lower number suggests that a model is less effective at identifying class 1 compared to class 0, highlighting a class imbalance in prediction accuracy.

A. Comparative analysis

This section compares the outcomes of three ML models on the sensor dataset in order to analyze the PdM model. Table 3 provides a comparative result of an ML model where the ANN model outperforms other models.

Table. 3 Accuracy Comparison between machine and deep learning models

Model	Accuracy
CART[25]	90.18
RF[26]	92
LR[27]	82
ANN	98

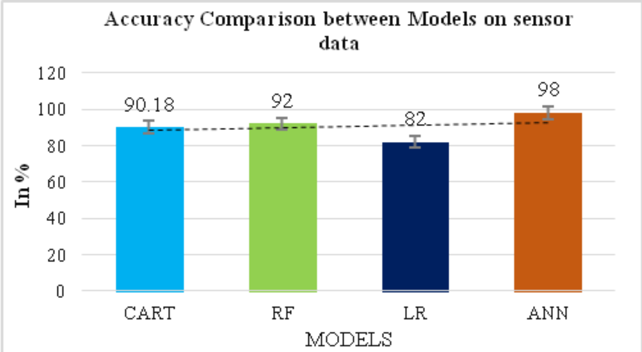

Fig. 8 Accuracy comparison between model

Figure 8 displayed an accuracy comparison of models. Comparing the models, the ANN leads with an accuracy of 98%, significantly outperforming others. The RF follows with an accuracy of 92%, showing strong performance but still lower than the ANN. The CART model achieves 90.18%, while the LR model has the lowest accuracy at 82%. This comparison highlights the ANN's superior classification capabilities relative to the other models.

V. CONCLUSION AND FUTURE STUDY

These days, smart production is becoming more dependent on the IIoT. One of the most important uses is PdM, which may identify a machine's present state and avert catastrophic malfunctions. It would be very costly to continually replace batteries across thousands of devices as the IoT expands. Furthermore, there is massive energy consumption due to a wireless transmission of original sensor data to a server for data processing. This study develops a predictive maintenance framework for industrial manufacturing using IoT sensor data. Various machine learning models, including ANN, CART, RF, and LR, are applied to the dataset, with the ANN model demonstrating superior performance, achieving 98% accuracy. The outcomes show that an ANN model is highly effective in classifying sensor data, significantly outperforming the other models. The research highlights an importance of robust data preprocessing, features election, and class balancing techniques in enhancing model performance for predictive maintenance tasks. The study has several limitations, including a relatively small dataset of 944 observations, which may limit a generalizability of findings, and a reliance on oversampling to address class imbalance, which could introduce data redundancy. Additionally, the use of data from a single IoT sensor source restricts the model's applicability to more diverse industrial settings. For future work, expanding the dataset, incorporating data from multiple sensors or industries, and exploring advanced deep learning models like CNNs or LSTMs could enhance performance.

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