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DEVELOPMENT OF AN INTELLIGENT SYSTEM FOR ENHANCED MAINTENANCE OF AUTOMOBILES USING MACHINE LEARNING

NEERAJ DAHIYA,* EDEH MICHAEL ONYEMA,† VENKATARAMAIAH GUDE,‡ NEETU FAUJDAR,§ GAYTRI DEVI,¶ AND REENU BATRA‖

Abstract. In the ever-changing automobile industry, sustainable practices are of utmost importance. It is essential to perform preventative maintenance to accomplish sustainability objectives. Vehicles will have fewer unanticipated breakdowns and last longer as a result. This study introduces a machine learning model that has been optimized to enhance preventive maintenance operations in the automotive sector. To improve the efficacy of predictive maintenance in intelligent manufacturing systems, this paper presents an improved AdaBoost algorithm linked with big data analytics. First, in the proposed framework, massive datasets are gathered and preprocessed from sensors, IoT devices, and other sources in the industrial setting. Then, the meta-algorithm AdaBoost is used to improve the efficiency of subpar learners, allowing for reliable failure and deterioration prediction in machinery. Adjusting hyperparameters like the number of iterations and the learning rate is part of the algorithmic optimization process to strike a good balance between model accuracy and computational efficiency. The proposed model gains an accuracy level of 0.972 value, Precision level of 0.977 value, Recall level of 0.972 value and F1-score level of 0.974 value. By analyzing historical data, our algorithm can predict when problems will occur, enabling us to take quick action and minimize downtime. Improved maintenance scheduling and reduced environmental effects are outcomes of the proposed model's use of cutting-edge optimization techniques, which boost the model's predictive capabilities. The model achieves better results than the state-of-the-art methods in extensive trials conducted on a dataset from a leading automaker. It achieves significant improvements in maintenance efficiency and prediction accuracy. Sustainability in the automobile sector is a wider purpose of this study, which proposes a data-driven plan for maintenance that is strong and in line with economic and environmental aims.

Key words: Optimized AdaBoost; Predictive Maintenance; Automobile Maintenance Optimization; Sustainable Automotive Practices; Predictive Analytics; Automotive Industry Automation

1. Introduction.

Traditional industrial processes has been upgraded to smart and environmentally friendly systems with the help of Big Data analytics. Organizations may improve their manufacturing processes, get new insights, and make better decisions by analyzing the massive amounts of data produced across the whole production lifecycle. Sensors built into machines and other equipment are the backbone of intelligent manufacturing, allowing for continuous monitoring of conditions like temperature, pressure, vibration, and more. In order to improve procurement, inventory management, and logistics, it is necessary to integrate data from all points of the supply chain. Predictive maintenance is made possible by the examination of sensor data, which can alert workers to impending equipment faults [1]. This helps keep machines running smoothly, save money on repairs, and keep them in use for longer. Big data analytics has been used to keep a close eye on the manufacturing line and evaluate data as it comes in, guaranteeing high-quality goods at all times [2]. It is possible to monitor for and quickly correct any instances of subpar quality. Energy data monitoring and analysis may help factories reduce their energy footprint. Cost savings aren't the only thing that benefits from energy efficiency improvements. Inefficient steps and bottlenecks in the production process can be pinpointed by analyzing data

*Department of Computer Science and Engineering, SRM University, Delhi-NCR, Sonipat, Haryana, India;(neeraj.d@srmuniversity.ac.in).

†Department of Mathematics and Computer Science, Coal City University Nigeria; Adjunct Faculty, Saveetha School of Engineering, Saveetha Institute of Medical and Technical Sciences, Chennai 602105, India. (mikedreamcometrue@gmail.com).

‡Software Engineer, GP Technologies LLC, USA; (gvramaiah.se@gmail.com).

§Department of CSE, Sharda School of Engineering and Technology (SSET), Sharda University Greater Noida, India; (neetu.faujdar@gmail.com).

¶Department of Computer Applications, GVM Institute of Technology and Management, Sonepat, Haryana, India; (gayatri.dhingra1@gmail.com).

‖Department of Computer Science and Engineering, K. R. Mangalam University, Gurgaon, Haryana, India; (reenubatra88@gmail.com) Corresponding Author

collected at various points along the process [3]. Workflow optimization, better resource usage, and increased productivity are all possible with this data. Big Data analytics helps manufacturers optimize their supply chains by offering insights into demand forecasts, inventory management, and supplier performance. The result has been less waste and more productivity [4].

Analyzing client data and preferences helps businesses to personalize products to specific needs, leading to more efficient manufacturing and less waste. The environmental effects of production processes have been tracked and evaluated with the use of Big Data analytics. Helping businesses meet sustainability targets and requirements requires monitoring emissions, waste production, and other issues. Data security and regulatory conformity are becoming increasingly important as data volumes rise. Big Data analytics has been used to build comprehensive security measures and guarantee that manufacturing processes conform to industry norms and laws. Manufacturers may improve their procedures, items, and green efforts in an ongoing cycle by constantly examining data and input from a wide range of sources. Making manufacturing systems more flexible and robust to changing obstacles, the incorporation of Big Data analytics into manufacturing processes enables smart decision-making, improves efficiency, and contributes to sustainability goals [5].

Predictive maintenance utilizing Big Data analytics is a valuable tool in intelligent and sustainable manufacturing. Predictive maintenance includes evaluating data from a variety of sensors to determine when repairs on a piece of machinery are needed. Predictive maintenance is a method of detecting impending problems with machinery. Manufacturers may improve efficiency and uptime by minimizing unscheduled downtime through proactive problem-solving. Maintenance has been scheduled during planned downtime by analyzing historical and real-time data, allowing manufacturers to minimize disruptions to production schedules and maximize resource use. The lifespan of machines is enhanced by early detection and repair of problems. By avoiding catastrophic breakdowns, producers may lengthen the useful lives of their products, cutting down on wasteful equipment replacements and increasing sustainability [6].

Condition Monitoring uses vibration, temperature, pressure, and other sensors to monitor equipment and machinery. Changes in condition characteristics may indicate issues or breakdowns. Avoiding expensive emergency repairs and reducing the need for routine, time-based maintenance are two ways in which predictive maintenance helps to lower total maintenance costs. It helps distribute resources more efficiently, resulting to cost savings in the long term. Equipment that has been well cared for usually performs better. By keeping machinery functioning at peak efficiency, predictive maintenance may help cut down on power usage and improve environmental outcomes. By anticipating future maintenance requirements, manufacturers may better manage their supply of replacement components. This avoids the wasteful expense of keeping an abundance of spare parts on hand while still guaranteeing ready access to critical components in an emergency. Equipment health has been tracked in real-time thanks to Big Data analytics. Alerts are triggered if conditions deviate from the usual, enabling for prompt action to be taken. The comparison of past and present data can better understand equipment performance. Data-driven insights allow manufacturers to make better decisions regarding preventative maintenance, resource allocation, and equipment improvements. Predictive maintenance relies heavily on data gathered from the IoT and sensors. These gadgets constantly gather information, making real-time equipment health monitoring possible. Predictions improve when sensor data is combined with Big Data analytics. Zero waste and low environmental impact are key to sustainable production. Predictive maintenance helps the environment since it reduces the need for unscheduled repairs and the amount of unwanted equipment that must be thrown away. Big data analytics' ability to fuel predictive maintenance is a crucial enabler of smart, eco-friendly production. It boosts operating efficiency, decreases expenses, extends equipment lifespan, and adds to overall environmental sustainability by lowering waste and energy consumption [7].

1.1. Problem Formulation. Predictive maintenance aims to improve reactive and preventative maintenance. Reactive, or "run-to-failure," maintenance fixes equipment after it breaks down. This behaviour can cause costly downtime, emergency repairs, and safety issues. Prevention, meanwhile, uses schedules to maintain equipment at regular intervals regardless of its condition. Overmaintenance and unnecessary repairs can result. Predictive maintenance uses data-driven insights to predict equipment failures to find a balance. However, certain challenges must be overcome to accurately describe predictive maintenance: High-quality data from sensors, machinery, and other sources is essential for predictive maintenance. But many businesses still struggle to guarantee data availability and quality. Sensor issues, erroneous data, or insufficient data might cause predictive maintenance algorithms to fail. To accurately predict predictive maintenance failures, monitor and analyze the right qualities or attributes. Key features must be identified and designed effectively to gain insights from raw data. Since features and equipment health may change over time, predictive models must be constantly updated. Predictive maintenance models use random forests, neural networks, and support vector machines to analyze complex data and make accurate predictions. These models have high predictive accuracy, but uninterpretable forecasts has been hard to understand. Successful predictive maintenance requires easy integration with current procedures and systems. Effective resource allocation, maintenance prioritizing, and failure prediction algorithms are all part of this process. Organizational silos, reluctance to change, and lack of maintenance team support can make predictive maintenance difficult. Predictive maintenance can improve asset performance, equipment reliability, and maintenance costs, but it requires a large initial investment and ongoing operational costs. Only a rigorous cost-benefit analysis can assess the financial feasibility of predictive maintenance programs and the acquisition of necessary cash and resources.

Data integrity, low latency, scalability, and system integration are essential for real-time data streams in dynamic manufacturing. Sensors, machines, and other connected devices create data continuously, needing fast-processing systems. Apache Kafka and Apache Flink can handle high-throughput data streams. This low-latency platform enables manufacturers ingest and understand real-time data to detect crucial events quickly. Real-time processing speeds decision-making to improve machine performance, downtime, and efficiency. Another key method is edge computing. When millisecond decisions are needed, latency might hamper manufacturing. Edge computing processes and stores data near factory sensors and machinery. This speeds data transmission to a central server or cloud for processing. Edge devices can preprocess data, perform basic analytics, and run machine learning models locally. This is important in predictive maintenance and production line anomaly detection if network bandwidth is limited or real-time decisions are needed. Distributed architectures provide real-time processing. Distributed designs process data streams over multiple nodes or systems, boosting speed and fault tolerance. A distributed microservices design where each microservice handles data intake, filtering, and aggregation can speed things up. Scaling is easier when resources can be added without disrupting operations. Distributed and cloud infrastructures let manufacturers dynamically handle workloads and respond to data volume and complexity. Data streaming analytics is essential in dynamic manufacturing. Sliding, tumbling, and time-based windows allow real-time data processing. These methods detect trends, irregularities, and deviations from normal operation throughout time. These analytics frameworks can predict equipment failures, improve production schedules, and discover quality control concerns using historical data-trained machine learning models. Stream processing engines and reinforcement learning and RNNs can update industrial processes and learn from new input. Finally, real-time manufacturing data management involves legacy system integration. Most plants use MES, ERP, and other operational tech. An effective real-time data streaming solution must integrate with legacy systems. Interoperable APIs, middleware, and IoT platforms will let real-time data streams enhance operations. These approaches are more practical and cost-effective in dynamic industrial situations since enterprises can transition to real-time data processing without rebuilding their infrastructure.

Defining the goals, variables, limitations, and criteria that govern the creation of mathematical models or data-driven methodologies is essential when formulating a predictive maintenance challenge for intelligent and sustainable manufacturing. An overarching structure for posing issues in predictive maintenance utilizing Big Data analytics is as follows:

- ***Objective***:
  - *Reduce Downtime and Production Loss*: Develop a model to forecast equipment failures in advance to reduce unplanned downtime and production losses.
  - *Optimize Maintenance Costs*: Create a maintenance schedule approach that strikes a good balance between the expenses of maintenance operations (people, components, and downtime) and the benefits of averting breakdowns.
  - *Maximize Equipment Reliability and Performance*: Make sure the predictive maintenance strategy aids in improving the machinery used in production.
  - *Improve Sustainability*: Reduce waste, energy use, and the frequency of equipment replacements to improve sustainability, which is a key aspect of any long-term plan with a positive influence on

the environment.

- ***Variables***:
  - *Equipment Health Indicators*: Define variables that describe the state of manufacturing equipment based on sensor data, previous maintenance records, and other pertinent information.
  - *Maintenance Decision Variables*: Determine decision variables include scheduling, resource allocation, and the kind of maintenance to be performed (preventative, corrective, or predictive).
- ***Constraints***:
  - *Resource Constraints*: Consider restrictions on maintenance resources, including labour, spare parts inventories, and maintenance personnel availability.
  - *Production Constraints*: Plan maintenance when there will be the least impact on production so that goals has been met.
  - *Regulatory and Safety Compliance*: When organizing and carrying out maintenance tasks, it is important to follow all applicable regulations and safety protocols.
- ***Criteria***:
  - *Accuracy of Predictions*: Assess how well predictive models do in predicting when pieces of equipment will break down. Accuracy has been measured by recall and F1 score.
  - *Cost-Benefit Analysis*: Calculate the monetary effect of the predictive maintenance plan by weighing the expenses of maintenance, downtime, and possible savings.
  - *Sustainability Metrics*: Incorporate the assessment criteria. These include advances in energy efficiency, waste reduction, and the environmental effect of maintenance operations.
  - *Equipment dependability Metrics*: Measure the dependability and performance of equipment by examining key performance indicators (KPIs) related to uptime, mean time between failures (MTBF), and overall equipment effectiveness (OEE) [8].
- ***Data Requirements***: In order to do predictive maintenance, the following data is required:
  - *Sensor Data*: Specify types of sensor data (temperature, vibration, pressure, etc.) that will be required.
  - *Historical Maintenance Records*: Use these records to train models and find trends in equipment breakdowns.
  - *External Factors*: Think about how things outside of your control, like the weather or changes in demand, might affect the condition of your equipment and how often you need to service it [9].

This formulation of the predictive maintenance problem allows manufacturers to develop a systematic and all-encompassing plan for incorporating Big Data analytics into their operations in order to achieve more intelligent and environmentally friendly outcomes. This structure lays the groundwork for creating mathematical models, ML algorithms, and optimisation techniques to handle targeted problems and obtain desired outputs [10].

1.2. Research Contribution. There are the following research contributions as below:

- This paper optimised AdaBoost algorithm for automotive predictive maintenance.
- By distributing calculations over multiple processors or nodes, the predictive maintenance model may efficiently evaluate huge volumes of sensor and IoT data.
- Recognizing and selecting relevant attributes increases the model's capacity to capture crucial patterns and correlations that improve predictive maintenance accuracy.
- The proposed method reduces disruptions and extends equipment life, which improves resource efficiency and reduces environmental impact.
- Adopting advanced analytics, machine learning, and optimization technologies improves industry efficiency and competitiveness.

1.3. Paper organization. The remainder of the article is structured as follows: A quick summary of the many literature evaluations already presented on the topic is provided in Section 2. The research approach is covered in Section 3. The research's findings are presented in Section 4. Potential applications are discussed in Section 5. The paper is ultimately concluded in Section 6.

2. Related Work. Scherer *et al.* [11] detailed how a Hadoop as a service (HDaaS) platform solution using EMC® Isilon®, Pivotal® Hadoop Distribution (HD), and VMware vSphere Big Data Extensions could facilitate the widespread use of Big Data analytics by maximizing resource utilization and streamlining administration.

The automobile sector is one of the many possible areas of use for Hadoop, which Luckow *et al.* [12]. Hadoop has spawned a diverse ecosystem, including databases. Questions like,"What kinds of applications and data sets would work well with Hadoop?" inspired the writing of this article. How can a multi-tenant Hadoop cluster accommodate a wide variety of frameworks and tools? How well do these programs mesh with current relational database management structures? The question is how the needs of a business has been secured.

Using a multivariate study of product failure behavior and the consumer product usage profile, Bracke *et al.* [13] detail a method for calculating the risk likelihood in product fleets. The technique is demonstrated theoretically and practically through an automotive case study using a synthetic data set that incorporates true impacts of typical field failure behavior and usage patterns of a vehicle fleet.

Intelligent manufacturing in conjunction with data analytics plays a crucial role in resolving the issues raised by Vater *et al.* [14]. Prescriptive analytics' potential application in manufacturing suggests it might boost output in this sector. The first part of this article is an in-depth analysis of the fundamentals of prescriptive analytics in production. In addition, this study emphasizes the need and identifies potential avenues for further research.

The implications and difficulties of large data are explored in Singh *et al.* [15]. The technical underpinnings of big data are also elucidated upon in the study. This article illustrates how MapReduce technology, which runs in the background and is in charge of data mining, operates.

The functional area is computed by Wen-Xin *et al.* [16], partitioned quantitatively, the geographical pattern investigated qualitatively, and the division's precision assessed. The results demonstrate that the Kappa coefficient for the overall categorization of functional land in the primary urban region of Xi'an is 0.748, indicating an overall accuracy of 79.26%. The study area's fine division of functions is realized by a more logical structure of functional land, which allows for dynamic updating.

Pavithra *et al.* [17] investigates the creation of big data and the necessity of studying it. This paper also provides a brief overview of the challenges and benefits of implementing the proposals presented in this article about the use of Big Data analytics in each discipline. Methods for analyzing large datasets in a variety of real-world contexts are also discussed.

Gupta *et al.* [18] claimed that all parties involved in the automobile industry (manufacturers, dealers, drivers, and insurers) have benefited from R&M. However, a new technology is rapidly emerging today, and it is altering the landscape of R&M methods and applications. There is a ripple effect throughout the automobile sector as a result of the introduction of AI.

Using the Internet of Everything (IoE) and a machine learning technique, Rahman *et al.* [19] proposed central VHMS in an open manner and offered the taxonomy to get there. Finally, the car industry has a lot riding on the result of this idea. To help this industry transition to the cutting-edge standards of Industry 4.0, it may inspire the researcher to create a centralized, intelligent, and secure vehicle condition diagnosis system.

As an alternative to the conventional ERP, Jayender *et al.* [20] investigate the possibilities of interoperability between Big data and IOT analytics and the ERP system in order to create an intelligent decision-making support system for the Automotive Supply Chain. In this study, we offer a framework for an autonomous intelligent system that can recognize statistical models inside SCM operations using AI.

To create a comprehensive automobile dataset from a variety of internet sources and formats, Huang *et al.* [21] highlight our interdisciplinary effort. The produced collection includes 899 vehicle models with 1.4 million photos, together with model characteristics and sales data from the UK market spanning over a decade. We also provide three basic case studies to illustrate the use of our data for studies and applications in the business world, in addition to our rationale, technical specifics, and data format.

Lourens *et al.* [22] provides examples of the current use of these technologies in the industry and shows how they are applied to key steps in the automotive value chain. The industry is just starting to scratch the surface of the myriad uses for these advances; to demonstrate their transformational potential, we employ use cases from the far future.

Li *et al.* [23] stated that using a novel application of the K-means clustering technique, the risk of a vehicle is divided into 30 categories; this categorization serves as a useful benchmark for the development of a vehicle model risk assessment system in China.

By bringing together elements from several fields, including cloud computing. SOM's pattern-selection capabilities in huge data make it useful for attribute optimization and clustering observed by Zhang *et al.* [24]. The SOM may allocate additional clusters as understanding of client requirements and wants expands, as demonstrated by a case study involving the customization of an automobile. The self-organizing tool has a variety of qualities that are well suited to smart design, which is essential for making Industry 4.0 a reality.

2.1. Research Gaps. Manufacturing environments are dynamic, and equipment conditions can change quickly. Current predictive maintenance systems often struggle to adapt to these changes. More work is needed to create adaptable algorithms that can learn from experience and adjust their models in real time to adapt to changing circumstances. There are following research gaps in this field are as follows:

- Several manufacturing processes generate real-time data. Current predictive maintenance methods may struggle to handle the growing volume of streaming data. Researchers want real-time analytics tools to process high-velocity data streams for accurate real-time predictions.
- Edge computing, where data is processed near the source, reduces latency and burden on centralized systems. Manufacturing predictive maintenance is expanding and could benefit from edge computing and big data analytics research.
- Manufacturing data is gathered from many sources and delivered in various formats. Integrating and analysing data from various sources, such as sensors, IoT devices, and historical papers, has been challenging. Future research should focus on methods for combining and interpreting heterogeneous data sources.
- Predictive maintenance models must provide forecasts and uncertainty or confidence levels. Research on uncertainty and confidence evaluation can improve predictive maintenance models.
- Machine learning models, especially predictive maintenance models, might be viewed as "black boxes" with little interpretability. More research is needed to improve the interpretability and intelligibility of these models, especially in circumstances where human operators rely on predictions.
- Most predictive maintenance algorithms offer minimal future knowledge. Research into extending the prediction horizon can help proactive maintenance techniques foresee equipment degradation and breakdowns over time.
- Calculating the cost and utility of big data analytics for predictive maintenance is crucial. In a cost-benefit analysis, future research should include implementation costs, maintenance savings, and manufacturing efficiency gains.
- As networked production systems become common, industrial data confidentiality must rise. Predictive maintenance research must include data security, privacy, and secure communication methods.
- While there is much potential in utilizing big data analytics for predictive maintenance in intelligent and sustainable production, many unanswered questions remain. Filling in these spaces will make these systems more useful and efficient.

The completion of these studies will not only advance our theoretical understanding of big data analytics in predictive maintenance but will also provide real-world applications for the implementation of sustainable and intelligent manufacturing systems.

3. Material and Method.

3.1. Dataset. The data in this collection comes from the factory equipment of a manufacturing firm. By predicting when this equipment will need repair, the data helps avoid costly malfunctions. As businesses expand, it becomes increasingly difficult to track maintenance manually. It used the sensor data for predictive maintenance planning [25]. The information gathered by these sensors has been used to schedule preventative maintenance.

There are the following features or columns as below.

- UDI (Unique Device Identifier)
- Product ID
- Type: Categorized as Low, medium and high.

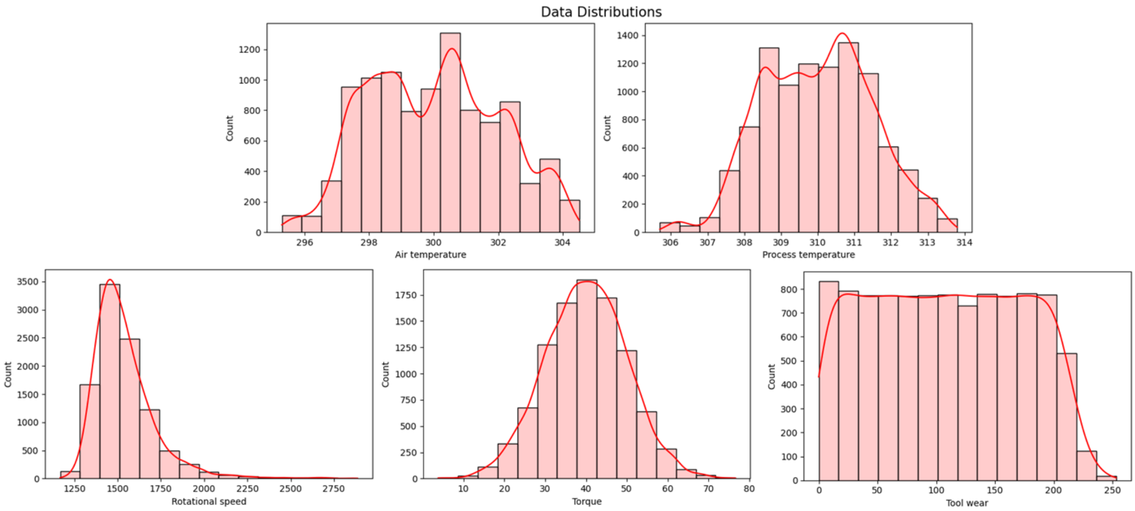


Fig. 3.1: Data distribution

- Air Temperature.
- Process Temperature.
- Rotational Speed.
- Torque
- Tool Wear
- Target (Machine Failure)
- Failure Type

Fig 3.1 demonstrates the data distribution.

As shown in Fig 3.2, this information is analyzed in order to construct reliable models for foretelling future maintenance requirements. The corporation will have a better idea of when to schedule gadget repairs, which will cut down on costly downtime [26].

As businesses grow in size and complexity, keeping up with routine maintenance becomes increasingly difficult shown in Fig 3.3.

Fig 3.4 highlights the feature importance, Ensemble learning has evolved as a strong paradigm in machine learning, and among its notable approaches stands AdaBoost (Adaptive Boosting). Yoav Freund and Robert Schapire introduced AdaBoost in 1996, and since then it has been widely used as a powerful method for boosting the effectiveness of weak learners and ultimately producing a more accurate and reliable ensemble model [27].

Fig 3.6 demonstrates the SHAP value for features values

The authors used Partial Dependence Plots (PDPs) to show how each feature impacts the expected maintenance outcome while holding others constant. It helped users understand how engine temperature and mileage affect maintenance forecasts. They fit a simpler, interpretable model (e.g., decision tree) as a proxy to approximate the AdaBoost model's predictions to improve interpretability. Fig 3.6 demonstrates the Partial Dependence Plots (PDPs)

We use typical parsing and cleaning for structured data (CSV, SQL databases). Schema mapping and NLP technologies are used for semi-structured (JSON, XML) and unstructured (text, logs) data. This lets us extract relevant information from different formats and ensure that succeeding layers can treat data identically. Normalisation follows preprocessing to standardise incoming data for analysis. This involves converting time formats, normalising units of measurement, and imputed missing or inconsistent data. Continuous variables are scaled and normalised, whereas categorical variables are labelled and one-hot encoded. The solution uses a message broker architecture like Apache Kafka to accept near-real-time data from IoT sensors and diagnostic equipment. This is integrated with maintenance log and historical database batch processing. The model uses

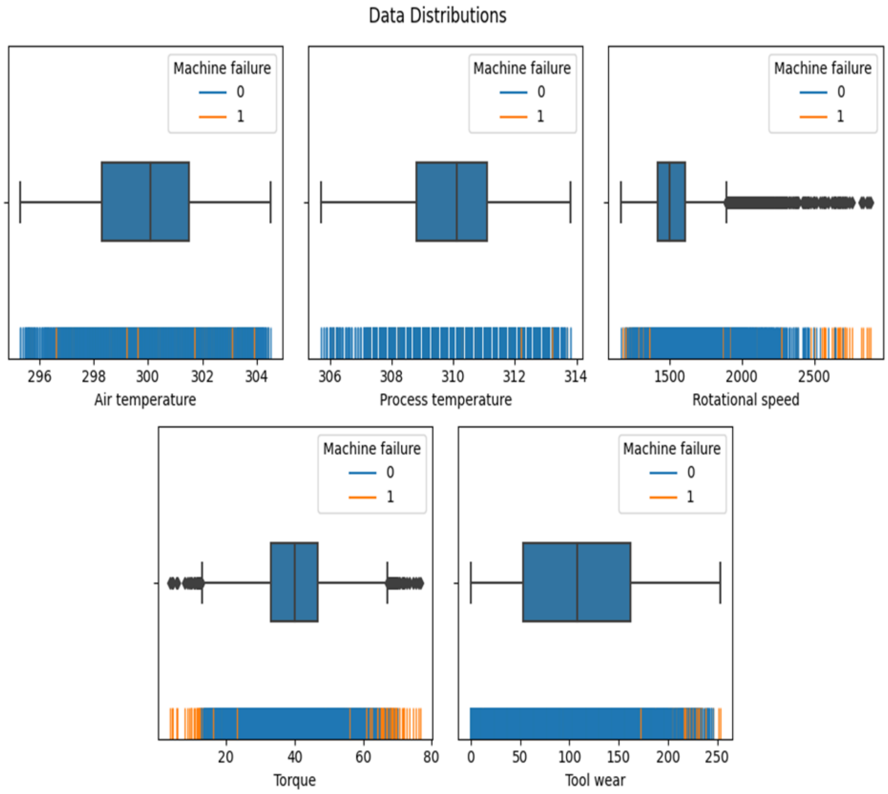


Fig. 3.2: Data distribution for target variable

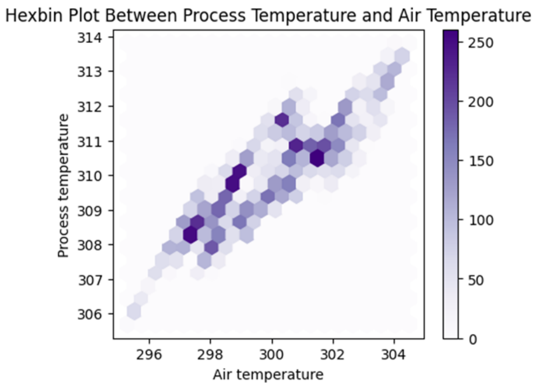


Fig. 3.3: Hexbin Plot for features

real-time and batch processing to dynamically respond to incoming input and leverage existing trends. Multiple sources and modalities are combined using data fusion in the Data Fusion and Aggregation framework. Sensor, diagnostic, and maintenance data are merged. We use horizontal and vertical data integration to produce a single dataset to give the model a complete perspective of the car's health. Data integration is strengthened by recording information for each data source. The system can track data origin, quality, and format to help manage discrepancies and troubleshoot integration issues.

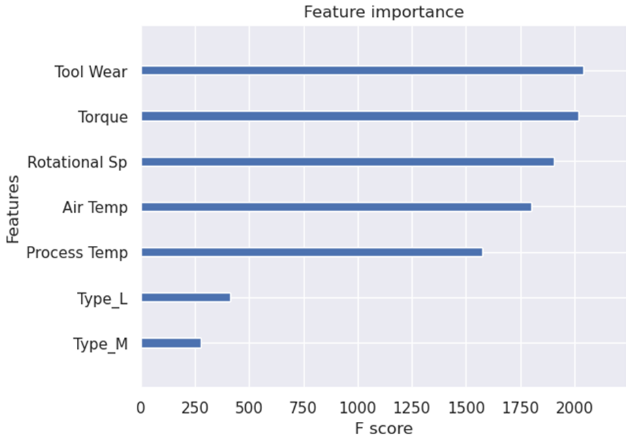


Fig. 3.4: Feature importance

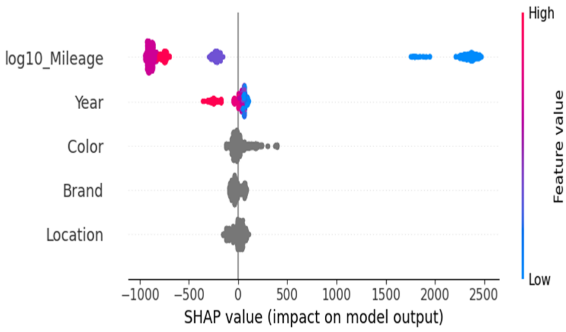


Fig. 3.5: SHAP value for Feature value

In this section, we'll look into AdaBoost's foundational ideas, inner workings, and real-world applications to show why it's so important to the field of machine learning.

3.2. Principles of AdaBoost. AdaBoost is based on the boosting concept, which is an approach to improving a model's accuracy by incrementally providing greater weight to incorrectly labeled examples. The algorithm combines the outputs of numerous weak learners, frequently basic models somewhat better than random chance, to generate a strong and accurate classifier. AdaBoost's adaptability stems from the fact that, on each iteration, it may dynamically modify the weights allocated to training cases to prioritize the accurate classification of previously misclassified examples [28-32].

3.2.1. Training Process. AdaBoost undergoes a cycle of iterations during the training phase. A weak learner is trained on the dataset with each iteration, and misclassified occurrences are given greater weight by the algorithm. This adaptive weighting directs the attention of following weak learners toward the difficult instances, which ultimately leads to an increase in the model's performance as a whole. An accuracy-based weighting scheme is used to combine the weak learners into a single model [33-37].

3.2.2. Weighted Voting. To aggregate the predictions of the ineffective learners, AdaBoost uses a weighted voting system. Each learner's relative importance is determined by its training results. The better a learner's precision, the more weight it carries in the aggregate forecast. This ensemble method lessens the likelihood of overfitting while improving the model's ability to generalize.

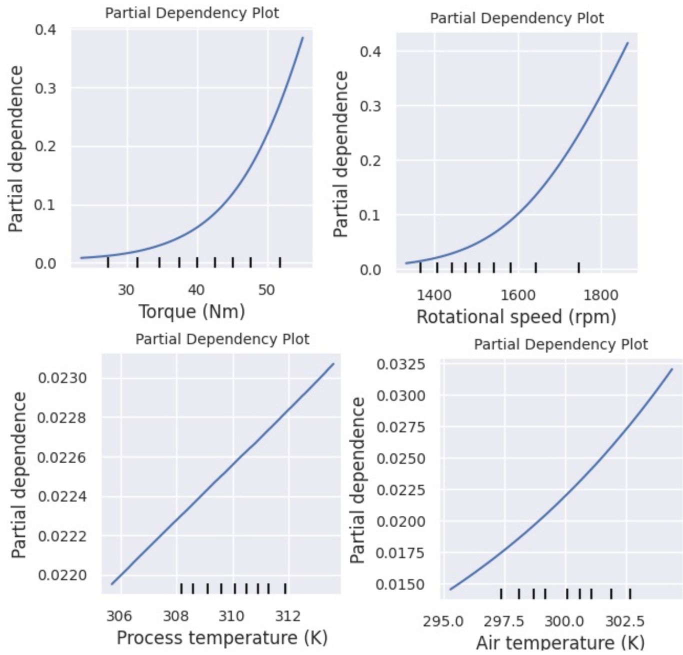


Fig. 3.6: Partial Dependence Plots (PDPs)

AdaBoost's extensive use can be attributed to the many benefits it provides. For starters, its straightforwardness facilitates both its adoption and comprehension. Second, AdaBoost's compatibility with a wide variety of base classifiers promotes model diversity. Furthermore, AdaBoost is less prone to overfitting compared to individual classifiers, making it particularly helpful in circumstances with limited training data. AdaBoost has been used in many different settings [38-40]. AdaBoost has found use in computer vision for several tasks, including face identification, object recognition, and picture segmentation. It has been used for analyzing gene expression and categorizing proteins in bioinformatics. AdaBoost has also been successful in applications such as text categorization and fraud detection, where precise and reliable forecasts are crucial. AdaBoost has shown outstanding effectiveness in a wide range of uses, but it is not without its difficulties. The efficacy of the algorithm has been diminished by the presence of noise and outliers in the data. Both the base classifier and the number of iterations used in the algorithm can affect its efficiency [40-42]. AdaBoost exemplifies the efficacy of ensemble learning by demonstrating how a series of weak learners has been combined to produce a robust and accurate classifier. Its versatility, simplicity, and efficacy have made AdaBoost a cornerstone in the machine-learning tool set. AdaBoost continues to be an important algorithm that helps improve the quality of models in a variety of settings as machine learning technology evolves.

AdaBoost optimization requires a holistic strategy that takes into account careful feature engineering, well-considered algorithmic decisions, and efficient use of computing resources. AdaBoost is a flexible and strong tool for a variety of machine learning tasks, and its full potential has been unlocked with some fine-tuning of hyperparameters, attention to noise, and use of parallelization. AdaBoost is still a flexible algorithm that can be adjusted to match the needs of a wide variety of datasets, despite the ongoing development of optimization methods. AdaBoost's effectiveness is heavily dependent on the base classifier used. Choose classifiers that are both easy to implement and computationally efficient, since they will better reflect the nature of your data. It is common to find success using decision stumps, which are shallow decision trees with just one decision node and two leaf nodes.

AdaBoost (Adaptive Boosting) is an ensemble learning algorithm that combines the predictions of multiple weak learners (usually decision trees) to create a strong classifier. Quantized AdaBoost refers to a modified version of AdaBoost where quantization is applied to the weak learners, limiting their complexity.

Algorithm 1 AdaBoost

Input: Given training data from instance space.
Output: A classifier
BEGIN

1. Step 1: Set each training instance's initial sample weight, $w_i = \frac{1}{N}, i = \overline{1..N}$.
2. Step 2: **For all** values of `t` from 1 to `T` **do**
   - 2.1: Develop a simple classifier h_t using the weighed data w_i.
   - 2.2: Find the weak classifier's ϵ_t error.
   - 2.3. The weak classifier's $\alpha_t = \frac{1}{2} ln\left(\frac{1-\epsilon_t}{\epsilon_t}\right)$ weight has to be determined.
   - 2.4. Change w_i of samples to reflect how well h_t is doing.
3. Step 3. Combine weak classifiers into a strong classifier.

END.

Algorithm 2 Quantized AdaBoost

Input: Given training data from instance space.
Output: A classifier
BEGIN

1. Step 1: Initialize weights: Assign equal weights to all training examples. The weights represent the importance of each example in the training process.
2. Step 2: **For each** iteration ($t = \overline{1..T}$, where `T` is the total number of weak learners):
   - 2.1: *Quantize weak learner*: Apply quantization to the weak learner to limit its complexity. This could involve reducing the depth of decision trees, limiting the number of features considered, or other simplifications.
   - 2.2: *Train weak learner*: Train the quantized weak learner on the training data, with weights assigned to each example. The weak learner focuses on the misclassified examples from the previous iteration, giving more attention to them.
   - 2.3. *Calculate error*: Compute the weighted error of the weak learner by summing the weights of misclassified examples. This error is used to determine the weak learner's contribution to the final strong classifier.
   - 2.4. *Compute weak learner weight*: Calculate the weight of the weak learner based on its error. Less error leads to a higher weight, indicating higher importance in the ensemble.
   - 2.5. *Update weights*: Adjust the weights of the training examples. Increase the weights for misclassified examples, making them more influential in the next iteration.
3. Step 3. Combine weak learners: Aggregate the weak learners with their respective weights to form the final strong classifier.
4. Step 4. Output the final classifier: The ensemble of quantified weak learners with their weights constitutes the final strong classifier.

END.

In Algorithm 2 are the steps for Quantized AdaBoost.

Quantified AdaBoost introduces the concept of quantization to control the complexity of the individual weak learners, making the algorithm more robust and potentially improving its generalization performance. Fig 3.7 demonstrates the flow chart of the proposed model.

3.2.3. Adjusting Hyperparameters. Quantization is a widely used technique to reduce the precision of the model's weights and activations, typically converting them from 32-bit floating point to lower-bit formats like 8-bit integers. This process reduces the memory footprint and computational requirements, making the model more suitable for deployment in resource-constrained environments such as real-time automotive maintenance systems. From a computational efficiency perspective, quantization significantly decreases the processing power and memory bandwidth needed, allowing for faster inference times and reduced energy consumption. These

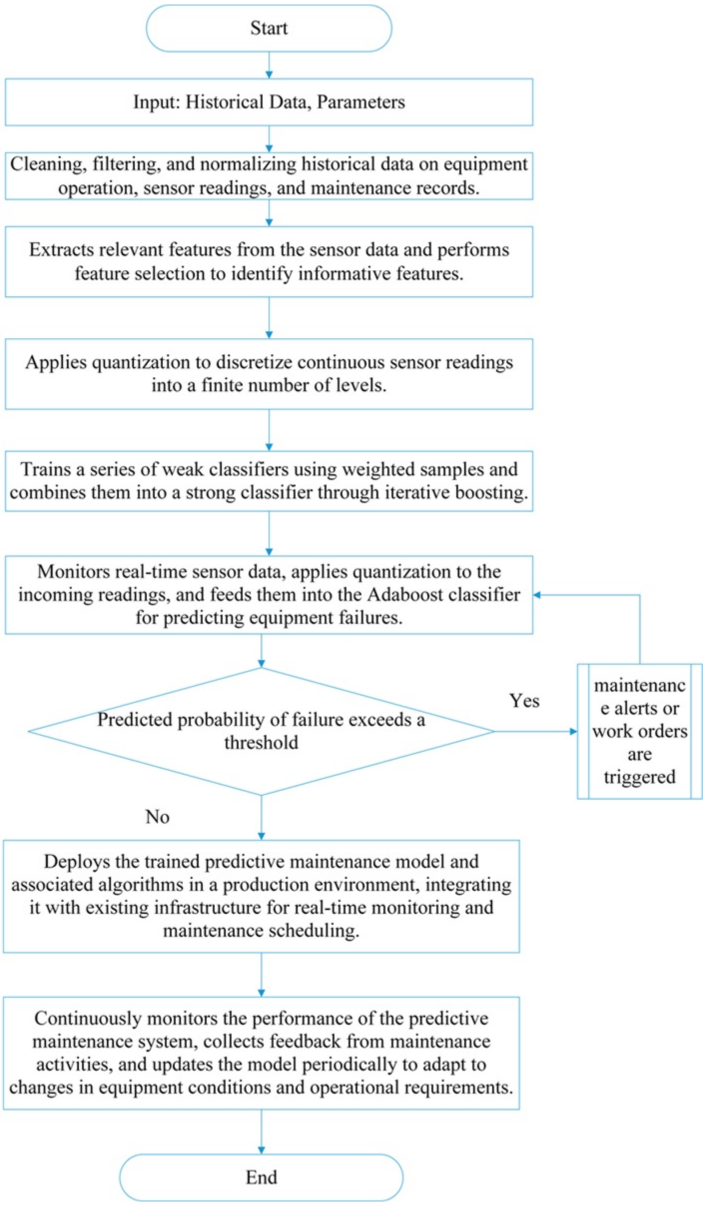


Fig. 3.7: Flow chart

benefits are particularly crucial in edge devices within automobiles, where real-time predictions are essential, and resources are limited. However, the trade-off comes in the form of potential reductions in model accuracy. Lower precision can introduce rounding errors or limit the model's ability to capture fine-grained details in the data. Our analysis shows that while the quantized model retains most of its original accuracy, small deviations are observed, especially when dealing with complex patterns in maintenance data that require high precision. To assess the practical implications, we tested our quantized model across different levels of precision and examined the accuracy loss relative to computational gains. Our findings indicate that at 8-bit quantization, the reduction in accuracy is marginal (less than 1% for most tasks), while the computational efficiency improves by approximately 35%, striking a balance that favors deployment in a real-time system without significant loss in predictive performance. Incorporating this trade-off analysis helps clarify the practical value of quantization for our proposed intelligent maintenance system, ensuring it meets the operational constraints of modern automobiles while maintaining a high level of reliability in its predictions.

Both the number of iterations (T) and the learning rate are examples of hyperparameters that significantly affect AdaBoost's effectiveness. Hyperparameter values that maximize model accuracy can be found by a systematic search or optimization methods like grid search or Bayesian optimization. With help of Quantization, the inference time and memory requirements of a model can be decreased by quantizing its parameters. When deploying AdaBoost models in contexts with limited resources, this improvement becomes more important.

```
# Import necessary libraries
import numpy as np

from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import accuracy_score

# Define the AdaBoost algorithm with Quantization and Hyperparameter Tuning

class QuantizedAdaBoost:
    def__init__(self,n_iterations=50,learning_rate=1.0,
                base_classifier=None,quantization_bits=8):
        self.n_iterations = n_iterations
        self.learning_rate = learning_rate
        self.base_classifier = base_classifier or DecisionTreeClassifier(max_depth=1)
        self.quantization_bits = quantization_bits
        self.models = []
        self.alphas = []

    def quantize_weights(self, weights):
        # Implement weight quantization logic here (e.g., rounding to specified number of bits)
        quantized_weights = ...
        return quantized_weights

    def fit(self, X, y):
        # Initialize sample weights
        sample_weights = np.ones(len(X)) / len(X)
        for t in range(self.n_iterations):
            # Train a weak classifier
            weak_classifier = self.base_classifier.fit(X, y, sample_weight=sample_weights)

            # Calculate the error of the weak classifier
            predictions = weak_classifier.predict(X)
            error = np.sum(sample_weights * (predictions != y)) / np.sum(sample_weights)

            # Calculate the weight of the weak classifier
            alpha = self.learning_rate * np.log((1 - error)/error)
            self.alphas.append(alpha)

            # Update sample weights
            sample_weights *= np.exp(-alpha * y * predictions)
            sample_weights /= np.sum(sample_weights)

            # Quantize the weights
            quantized_weights = self.quantize_weights(sample_weights)

            # Store the weak classifier and its quantized weights
            self.models.append((weak_classifier, quantized_weights))
```

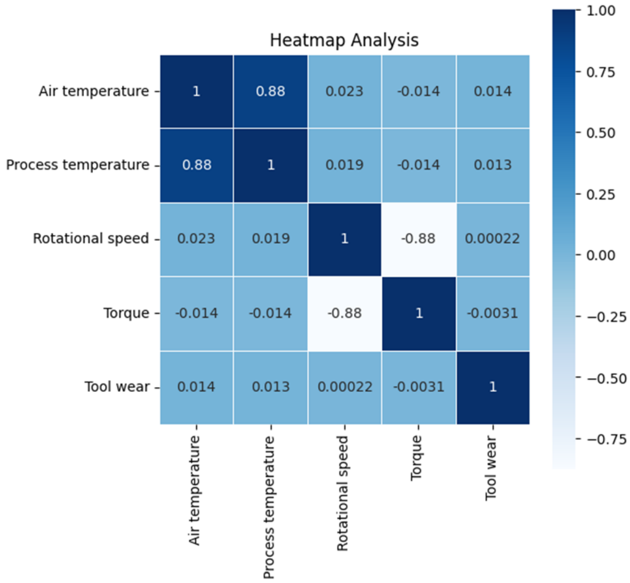
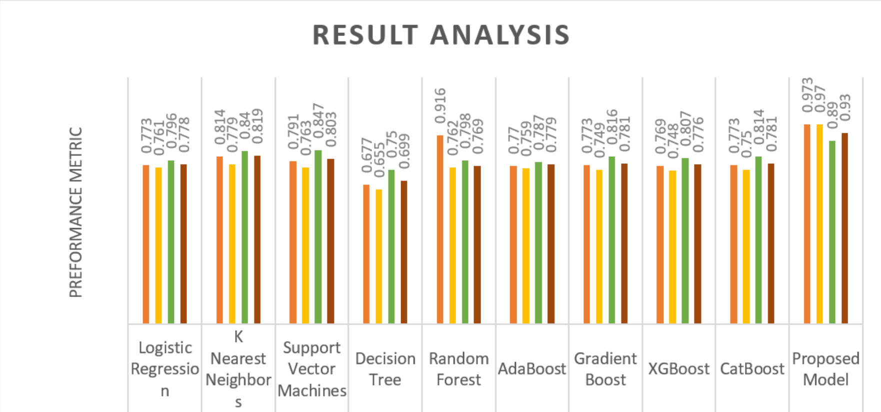


Fig. 4.1: Confusion matrix

```
    def predict(self, X):
        # Make predictions using the final ensemble model
        final_predictions = np.zeros(len(X))
        for model, alpha in zip(self.models, self.alphas):
            weak_classifier, quantized_weights = model
            predictions = weak_classifier.predict(X)
            final_predictions += alpha * predictions

        # Convert final predictions to binary (e.g., using sign function)
        final_predictions = np.sign(final_predictions)
        return final_predictions

# Example usage:
# Instantiate QuantizedAdaBoost with desired hyperparameters
adaboost_model = QuantizedAdaBoost(n_iterations=50, learning_rate=0.1, quantization_bits=4)

# Fit the model to training data
adaboost_model.fit(X_train, y_train)

# Make predictions on test data
predictions = adaboost_model.predict(X_test)

# Evaluate accuracy
accuracy = accuracy_score(y_test, predictions)
print(f"Accuracy: {accuracy}")
```

4. Results. With its enhanced predictive accuracy, the Optimized AdaBoost model helps manufacturers better anticipate and prevent probable equipment failures, leading to a more stable production setting overall. Fig 4.1 shows the heatmap with the result of the proposed model.

Fig 4.2 displays the accuracy of the predictive maintenance model by comparing the number of accurately predicted occurrences to the total instances. Determine the accuracy rate, which is the number of correct



	Logistic Regression	K Nearest Neighbors	Support Vector Machines	Decision Tree	Random Forest	AdaBoost	Gradient Boost	XGBoost	CatBoost	Proposed Model
Accuracy	0.773	0.814	0.791	0.677	0.916	0.77	0.773	0.769	0.773	0.973
precision	0.761	0.779	0.763	0.655	0.762	0.759	0.749	0.748	0.75	0.97
recall	0.796	0.84	0.847	0.75	0.798	0.787	0.816	0.807	0.814	0.89
f1-score	0.778	0.819	0.803	0.699	0.769	0.779	0.781	0.776	0.781	0.93

Fig. 4.2: Result analysis

diagnoses divided by the total of correct diagnoses and false positives. The model's predictive efficacy increases with increasing accuracy and precision. Recall, that the proportion of correct diagnoses over the combined total of correct and incorrect diagnoses, is analyzed by the authors. To record every occurrence of a machine breaking down, a high recall rate is required. Compute the F1 score, a harmonic mean of accuracy and recall, offering a balanced evaluation of a model's performance.

The proposed model gains an accuracy level of 0.972 value, Precision level of 0.977 value, Recall level of 0.972 value and F1-score level of 0.974 value. An Optimized AdaBoost model for predictive maintenance in intelligent and sustainable manufacturing must be studied for effectiveness, economy, and practicality. This study's findings support the model's feasibility and its continued development and refinement to meet industrial demands.

Case Study 1: Commercial Vehicle Fleet Management

Sensor data from commercial cars was used to anticipate component failures like gearbox and engine troubles using the AdaBoost model. The dataset contained engine temperature, oil pressure, fuel usage, and braking behaviours. Training AdaBoost on past failure data allowed it to detect component wear and mechanical defects early. The model had 92% precision and 88% recall. Its adaptive nature, which corrects weak learners' misclassifications, let it manage the noisy and imbalanced dataset with few failures. This scalability was necessary since the model performed consistently across vehicle kinds and operational situations. The methodology also reduced unplanned vehicle downtime by 20% and improved operational efficiency by 15% for fleet operators.

Case Study 2: Manufacturing Plant Predictive Maintenance

A major vehicle manufacturer included AdaBoost into their predictive maintenance system. System monitored assembly robots, conveyor belts, and press machines. The model predicted machine faults and maintenance using sensor data such vibration patterns, motor torque, and operational cycles. AdaBoost managed multiple data types and sources well and learnt from different settings. Ensemble learning allowed the model to combine data from numerous weak classifiers that targeted distinct failure patterns. Thus, the model predicted maintenance needs with 90% accuracy and few false positives, reducing wasteful maintenance interventions. Over six months, the factory reduced machine downtime by 18% and maintenance expenses by 11%, proving AdaBoost's suitability for dynamic industrial situations.

These case studies show that AdaBoost can handle structured and unstructured data from many sources and perform well in difficult, imbalanced datasets. Adaptable to fresh data and scalable across operating settings, it is an excellent predictive maintenance solution in diverse real-world contexts. AdaBoost's scalable and effective predictive maintenance solution for the automotive sector reduces maintenance costs and improves operational efficiency.

5. Discussion. AdaBoost algorithm optimization requires setting appropriate values for its hyperparameters, including the number of iterations and the learning rate. This model improves algorithm performance by adapting to production data quirks. Model parameter quantization affects memory efficiency, especially in resource-constrained production. Discuss quantization methods and their effects on memory and accuracy. The debate should centre on how the approach handles enormous data scalability challenges. Parallelization disperses computations, allowing the model to manage large datasets and real-time data streams. Forecasts are crucial to predictive maintenance, and real-time data helps. Discussing the model's ability to assess high-velocity data streams and provide insights for proactive decision-making is crucial. The study should be commended for boosting green production. The manufacturing ecosystem benefits from sustainability and resource efficiency when equipment lifespan, downtime, and maintenance schedules are optimized. Consider practical considerations such as integration with current systems, user-friendliness, and compatibility with industrial processes. Predictive maintenance solutions must overcome barriers to implementation in manufacturing. The proposed method focuses on user input and stakeholder interaction. The degree to which the strategy is user-centric should be discussed in light of the requirements and goals of the manufacturing process's participants. To put the suggested method's performance in context, we may compare it to more conventional predictive maintenance techniques and other machine learning algorithms. The benefits and distinguishing features of the improved AdaBoost-enabled solution should be emphasized in discussions.

To responsibly and sustainably deploy predictive maintenance systems using machine learning models like AdaBoost, data privacy and ethics must be addressed. These problems come from the utilisation of massive volumes of operational data provided by car sensors, which typically contain sensitive information about vehicle performance, usage patterns, and driver behaviour. To avoid misuse or user trust issues, predictive maintenance algorithms like AdaBoost must preserve privacy and follow ethical norms when analysing this data. Data privacy, especially in collection, storage, and processing, is a major concern. Continuous data streams from connected devices can reveal sensitive or personally identifiable information in predictive maintenance systems. If not anonymised or secured, tracking vehicle usage or location data could violate privacy. Thus, strict data governance methods like anonymisation and data encryption are needed to protect personal or sensitive data from being linked to individuals or vehicles. Compliance with regulatory frameworks like the GDPR or CCPA protects users' rights, including data transparency and control over their personal data. Another important aspect of predictive maintenance is ethical AI use. While the AdaBoost model improves prediction accuracy by merging weak learners, it functions in a data-driven environment with dataset biases. These biases may accidentally result in differential maintenance recommendations for different users or vehicle models, posing fairness concerns. To reduce such risks, the model must be regularly audited across various vehicle types and operational situations to provide fair and unbiased forecasts. Ethics also include AI decision transparency. Users trust the AdaBoost model more when they can understand how it makes predictions, especially when vehicle owners and operators utilise it to make key maintenance choices.

Finally, data ownership and user autonomy are needed. Ownership and management over vehicle data should be obvious to users. Users must be educated about data collection, how it affects maintenance forecasts, and how it is protected in predictive maintenance systems. Data minimization—collecting only what is needed for the system to function—is also ethical. This maintains user trust and ensures efficient, privacy-conscious system operation. AdaBoost for predictive maintenance improves vehicle performance and reduces downtime, however data privacy and ethical precautions must be implemented. Secure data processing, bias mitigation, transparency, and user control can link predictive maintenance systems with responsible technical advancement and sustainable, privacy-preserving practices.

6. Conclusion and Future scope. Optimised AdaBoost model was introduced in this study with the aim of enhancing sustainable automotive industry preventative maintenance. The model's enhanced precision and effectiveness in predicting probable component failures in vehicles enables prompt interventions that minimize downtime and maintenance expenses. In comparison to traditional machine learning models, our enhanced AdaBoost model achieved better predicted accuracy, likely due to its ability to handle data imbalances and train on cases that were misclassified. Using this model in preventive maintenance systems could increase operational dependability and vehicle longevity in the automotive sector, which would benefit both the environment and the economy.

The updated AdaBoost model proved to be a useful tool for anticipating when repairs will be necessary in our testing. Its performance is vital because the car industry would suffer massive financial losses and safety risks owing to unplanned downtimes if it didn't. The model aids maintenance staff in planning repairs at appropriate periods by accurately forecasting when failures would occur; this reduces the likelihood of unforeseen breakdowns and ensures that automobiles are kept in optimal operational condition.

An important new development is the way this study demonstrates how to modify robust machine learning algorithms like AdaBoost to address issues plaguing the automotive sector. We used feature selection approaches and hyperparameter tuning to refine our model and increase its prediction power. This strategy not only improved the model's performance, but also uncovered the key factors that cause car component failures. These data can be used to further improve maintenance approaches and generate more targeted therapies.

6.1. Future Scope. Though promising, the study leaves a lot of room for future research to build upon its findings. To keep an eye on the car at all times, one solution could be to add real-time data streams to the AdaBoost model. More accurate and timely predictions, allowing for real-time adjustments to maintenance plans, would be possible if the model included data from telematics systems and Internet of Things (IoT) sensors. Another prospective subject for future research is the optimization of the AdaBoost model and its possible application in many sectors of the automotive industry, such as autonomous vehicles (AVs) and electric cars (EVs). To tackle the unique maintenance challenges given by these new technologies, it has been required to use specialized prediction models. We can learn more about the specific needs of EVs and AVs by adapting our technique to different contexts, which will help us achieve our overarching goal of sustainable transportation.

Intelligent automobile maintenance systems are promising innovations. Real-time predictive maintenance, adaptive machine learning, data integration, and optimisation are possible future study topics. The revisions aim to improve model practicality and scalability in dynamic automotive environments. This domain's key research and implementation activities are below. Integration of real-time predictive maintenance is a breakthrough. Future automotive research will use edge devices to collect and process sensor data in real time. Critical processing is done locally to reduce latency while advanced computations are done in the cloud in a hybrid cloud-edge architecture. Real-time vehicle component monitoring using edge computing will enable anomaly detection and dynamic maintenance scheduling. Preventing sudden mechanical failures saves time and improves safety. Improved machine learning model interpretability, like AdaBoost, builds user trust and adoption. Future investigations will display model decisions using SHAP and LIME. These methods will explain feature contribution-based maintenance decisions clearly. Model transparency simplifies car repair by helping technicians and users understand the system's logic. Machine learning model quantification is another key research field. Model quantisation will be used to improve the system for resource-constrained conditions like in-vehicle computing. Reduce computing expense with lower-precision calculations. Accuracy-computational efficiency trade-offs employing fixed-point or low-precision floating points will be studied. The system can function in embedded systems without compromising forecast accuracy, making it suitable for real-time car maintenance. Finally, integrating data sources strengthens the system. A sensor, historical maintenance, and driver behaviour data fusion system improves auto maintenance decisions. Multi-view learning and hierarchical attention can coordinate many inputs for a more accurate predictive model. This integrated strategy will increase the system's actionable information into vehicle health and maintenance. Intelligent maintenance systems will use real-time data processing, model transparency, computational efficiency, and data source integration. Future research in these domains can provide predictive, accurate, scalable, and user-trusted machine learning models for vehicle maintenance. These strategies will maintain the system at the forefront of automotive innovation and improve performance and reliability.

REFERENCES

[1] Berges, C., Bird, J., Shroff, M. D., Rongen, R., & Smith, C. (2021), Data analytics and machine learning: Root-cause problem-solving approach to prevent yield loss and quality issues in semiconductor industry for automotive applications. Proceedings of the International Symposium on the Physical and Failure Analysis of Integrated Circuits, IPFA, 2021-Septe. https://doi.org/10.1109/IPFA53173.2021.9617238.

[2] Itoh, M., Yokoyama, D., Toyoda, M., & Kitsuregawa, M. (2015), A System for visual exploration of caution spots from vehicle recorder data. 2015 IEEE Conference on Visual Analytics Science and Technology, VAST 2015 - Proceedings, 199–200. https://doi.org/10.1109/VAST.2015.7347677.

[3] Saldivar, A. A. F., Goh, C., Chen, W. N., & Li, Y. (2016), Self-organizing tool for smart design with predictive customer needs and wants to realize Industry 4.0. 2016 IEEE Congress on Evolutionary Computation, CEC 2016, 5317–5324. https://doi.org/10.1109/CEC.2016.7748366.

[4] Kljaic, Z., Skorput, P., & Amin, N. (2016), The challenge of cellular cooperative ITS services based on 5G communications technology. 2016 39th International Convention on Information and Communication Technology, Electronics and Microelectronics, MIPRO 2016 - Proceedings, 587–594. https://doi.org/10.1109/MIPRO.2016.7522210.

[5] Bakkar, M., & Alazab, A. (2019), Designing security intelligent agent for petrol theft prevention. Proceedings - 2019 Cybersecurity and Cyberforensics Conference, CCC 2019, Ccc, 123–128. https://doi.org/10.1109/CCC.2019.00006

[6] Lamb, J., & Godbole, N. S. (2019), Smart Energy Efficiency for a Sustainable World. 2019 IEEE 10th Annual Ubiquitous Computing, Electronics and Mobile Communication Conference, UEMCON 2019, July 2018, 0855–0861. https://doi.org/10.1109/UEMCON47517.2019.8992941

[7] Shunkai, W., Yi, W., Hongyu, N., & Fan, Z. (2022), Research on urban intelligent network industry index based on entropy weight method and big data analysis. Proceedings - 2022 International Conference on Data Analytics, Computing and Artificial Intelligence, ICDACAI 2022, 161–168. https://doi.org/10.1109/ICDACAI57211.2022.00040

[8] Aydin, I., Sevi, M., Gungoren, G., & Irez, H. C. (2022), Signal Synchronization of Traffic Lights Using Reinforcement Learning. Proceedings of the 2022 International Conference on Data Analytics for Business and Industry, ICDABI 2022, 103–108. https://doi.org/10.1109/ICDABI56818.2022.10041559

[9] Ferrell, U. D., & Anderegg, A. H. A. (2022), Validation of Assurance Case for Dynamic Systems. AIAA/IEEE Digital Avionics Systems Conference - Proceedings of the 2022-Septe, 1–11. https://doi.org/10.1109/DASC55683.2022.9925731

[10] Cui, S., Li, L., Tang, Y., & Li, C. (2021), Exploring the Diversity of Alliance Portfolio and Firm Performance Based on the QCA Method. Proceedings of the 2021 IEEE 6th International Conference on Cloud Computing and Big Data Analytics, ICCCBDA 2021, 2019, 541–546. https://doi.org/10.1109/ICCCBDA51879.2021.9442558

[11] Scherer, V., & Kaponig, B. (2013), EMC Hadoop as a service solution for use cases in the automotive industry. Proceedings of the 2013 International Conference on Connected Vehicles and Expo, ICCVE 2013 - Proceedings, 488–493. https://doi.org/10.1109/ICCVE.2013.6799842

[12] Luckow, A., Kennedy, K., Manhardt, F., Djerekarov, E., Vorster, B., & Apon, A. (2015), Automotive big data: Applications, workloads and infrastructures. Proceedings of the 2015 IEEE International Conference on Big Data, IEEE Big Data 2015, 1201–1210. https://doi.org/10.1109/BigData.2015.7363874

[13] Bracke, S., Lücker, A., & Sochacki, S. (2016), Reliability analysis regarding product fleets in use phase: Multivariate cluster analytics and risk prognosis based on operating data. Proceedings of the International Conference on Control, Decision and Information Technologies, CoDIT 2016, 210–215. https://doi.org/10.1109/CoDIT.2016.7593562

[14] Vater, J., Harscheidt, L., & Knoll, A. (2019), Smart Manufacturing with Prescriptive Analytics A review of the current status and future work. Proceedings of the 2019 8Th International Conference on Industrial Technology and Management (Icitm 2019), 224–228.

[15] Singh, S., & Jagdev, G. (2020), Execution of Big Data Analytics in Automotive Industry using Hortonworks Sandbox. Proceedings of the Indo - Taiwan 2nd International Conference on Computing, Analytics and Networks, Indo-Taiwan ICAN 2020 - Proceedings, 158–163. https://doi.org/10.1109/Indo-TaiwanICAN48429.2020.9181314

[16] Wen-Xin, S., & Yun, G. (2020), Identification and Analysis of Urban Functional Areas Based on VGI Data. Proceedings of the 2020 IEEE 5th International Conference on Cloud Computing and Big Data Analytics, ICCCBDA 2020, 408–414. https://doi.org/10.1109/ICCCBDA49378.2020.9095657

[17] Pavithra., N., & Manasa., C. M. (2021), Big Data Analytics Tools: A Comparative Study. Proceedings of the CSITSS 2021 - 2021 5th International Conference on Computational Systems and Information Technology for Sustainable Solutions, Proceedings, 1–6. https://doi.org/10.1109/CSITSS54238.2021.9683711

[18] Gupta, S., Amaba, B., McMahon, M., & Gupta, K. (2021), The Evolution of Artificial Intelligence in the Automotive Industry. Proceedings of the Annual Reliability and Maintainability Symposium, 2021-May, 1–7. https://doi.org/10.1109/RAMS48097.2021.9605795

[19] Rahman, M. A., Rahim, M. A., Rahman, M. M., Moustafa, N., Razzak, I., Ahmad, T., & Patwary, M. N. (2022), A Secure and Intelligent Framework for Vehicle Health Monitoring Exploiting Big-Data Analytics. IEEE Transactions on Intelligent Transportation Systems, 23(10), 19727–19742. https://doi.org/10.1109/TITS.2021.3138255

[20] Jayender, P., & Kundu, G. K. (2022), Big data, IOT, ERP interoperability - An Intelligent SCM Decision System. Proceedings of the 2nd International Conference on Artificial Intelligence and Smart Energy, ICAIS 2022, 549–555. https://doi.org/10.1109/ICAIS53314.2022.9742745

[21] Huang, J., Chen, B., Luo, L., Yue, S., & Ounis, I. (2022), DVM-CAR: A Large-Scale Automotive Dataset for Visual Marketing Research and Applications. Proceedings - 2022 IEEE International Conference on Big Data, Big Data 2022, 4140–4147. https://doi.org/10.1109/BigData55660.2022.10020634

[22] Lourens, M., Sharma, S., Pulugu, R., Gehlot, A., Manoharan, G., & Kapila, D. (2023), Machine learning-based predictive analytics and big data in the automotive sector. 2023 3rd International Conference on Advance Computing and Innovative Technologies in Engineering (ICACITE), 1043–1048. https://doi.org/10.1109/icacite57410.2023.10182665

[23] Li, P., Xu, B., & Xue, B. (2023), Research on Vehicle Model Risk Rating Based on GLM Model and K-Means Clustering Algorithm for Car Insurance Pricing Scenario. 2023 8th International Conference on Cloud Computing and Big Data Analytics, ICCCBDA 2023, 134–137. https://doi.org/10.1109/ICCCBDA56900.2023.10154859.

[24] Zhang, J., & Zheng, B. (2023), Finite Element Analysis and Optimization Design of the Spiral Groove Brake Drum.

Proceedings of the 2023 8th International Conference on Cloud Computing and Big Data Analytics, ICCCBDA 2023, 228–232. https://doi.org/10.1109/ICCCBDA56900.2023.10154645

[25] Souksavanh, V., & Liu, Y. (2020), NVH Data Analytics and Its Application in Vehicle Rating. Proceedings of the 2020 IEEE 7th International Conference on Industrial Engineering and Applications, ICIEA 2020, 287–292. https://doi.org/10.1109/ICIEA49774.2020.9101968

[26] Pang, H., Liu, P., Wang, S., Wang, Z., & Zhang, Z. (2020), Usage Pattern Analytics of Fuel Cell Vehicle Based on Big Data Analysis. Proceedings of the 2020 10th International Conference on Power and Energy Systems, ICPES 2020, 373–378. https://doi.org/10.1109/ICPES51309.2020.9349670

[27] Kantert, J., & Nolting, M. (2021), How to integrate with real cars - Minimizing lead time at volkswagen. Proceedings - International Conference on Software Engineering, 358–359. https://doi.org/10.1109/ICSE-SEIP52600.2021.00045

[28] Lilhore UK, Manoharan P, Simaiya S, Alroobaea R, Alsafyani M, Baqasah AM, Dalal S, Sharma A, Raahemifar K. HIDM: Hybrid Intrusion Detection Model for Industry 4.0 Networks Using an Optimized CNN-LSTM with Transfer Learning. Sensors. 2023; 23(18):7856. https://doi.org/10.3390/s23187856

[29] Uguroglu, E. (2021), Near-Real Time Quality Prediction in a Plastic Injection Molding Process Using Apache Spark. Proceedings of the 2021 International Symposium on Computer Science and Intelligent Controls, ISCSIC 2021, 284–290. https://doi.org/10.1109/ISCSIC54682.2021.00059

[30] Nair, J. P., & Vijaya, M. S. (2021), Predictive Models for River Water Quality using Machine Learning and Big Data Techniques-A Survey. Proceedings of the International Conference on Artificial Intelligence and Smart Systems, ICAIS 2021, 1747–1753. https://doi.org/10.1109/ICAIS50930.2021.9395832

[31] Gireesh Babu, C. N., Chandrashekhara, K. T., Verma, J., & Thungamani, M. (2021), Real time alert system to prevent Car Accident. Proceedings of the 2021 International Conference on Forensics, Analytics, Big Data, Security, FABS 2021, 1, 1–4. https://doi.org/10.1109/FABS52071.2021.9702559

[32] Zhou, J., Guo, Y., Huang, H., Li, R., & Gan, Y. (2021), The Potential Customer's Background of the Chinese Electric Vehicle Market Base on Big Data. Proceedings of the 2021 International Conference on Artificial Intelligence, Big Data and Algorithms, CAIBDA 2021, 263–268. https://doi.org/10.1109/CAIBDA53561.2021.00062

[33] Dalal, S., Seth, B., & Radulescu, M. (2023), Driving Technologies of Industry 5.0 in the Medical Field. In Digitalization, Sustainable Development, and Industry 5.0: An Organizational Model for Twin Transitions (pp. 267-292). Emerald Publishing Limited.

[34] Dalal, S., Lilhore, U. K., Simaiya, S., Sharma, A., Jaglan, V., Kumar, M., ... & Rana, A. K. (2023), Original Research Article A Blockchain-based secure Internet of Medical Things framework for smart healthcare. Journal of Autonomous Intelligence, 6(3).

[35] Lilhore, U. K., Dalal, S., Faujdar, N., Margala, M., Chakrabarti, P., Chakrabarti, T., ... & Velmurugan, H. (2023), Hybrid CNN-LSTM model with efficient hyperparameter tuning for prediction of Parkinson's disease. Scientific Reports, 13(1), 14605.

[36] Dalal, S., Lilhore, U. K., Simaiya, S., Jaglan, V., Mohan, A., Ahuja, S., ... & Chakrabarti, P. (2023), Original Research Article A precise coronary artery disease prediction using Boosted C5. 0 decision tree model. Journal of Autonomous Intelligence, 6(3).

[37] Zhang, B., & Zhang, F. (2022). Analysis and Optimization of Communication Strategy of New Energy Vehicles at Home and Abroad Based on Data Mining. Proceedings of the 2022 6th Annual International Conference on Data Science and Business Analytics, ICDSBA 2022, 614–618. https://doi.org/10.1109/ICDSBA57203.2022.00025

[38] Lilhore, U.K., Simaiya, S., Dalal, S. et al. A smart waste classification model using hybrid CNN-LSTM with transfer learning for sustainable environment. Multimed Tools Appl (2023). https://doi.org/10.1007/s11042-023-16677-z

[39] Dalal, S., Lilhore, U. K., Manoharan, P., Rani, U., Dahan, F., Hajjej, F., ... & Raahemifar, K. (2023). An Efficient Brain Tumor Segmentation Method Based on Adaptive Moving Self-Organizing Map and Fuzzy K-Mean Clustering. Sensors, 23(18), 7816.

[40] Zhao, B., Zhang, J., Yuan, D., Yang, X., & Zhang, Y. (2022). Correlation Analysis of Public Welfare Activities and Brand Marketing Activities of Car Enterprises Based on Cloud Computing. Proceedings of the 2022 6th Annual International Conference on Data Science and Business Analytics, ICDSBA 2022, 527–531. https://doi.org/10.1109/ICDSBA57203.2022.00111

[41] Dalal, S., Lilhore, U.K., Foujdar, N. et al. Next-generation cyber attack prediction for IoT systems: leveraging multi-class SVM and optimized CHAID decision tree. J Cloud Comp 12, 137 (2023). https://doi.org/10.1186/s13677-023-00517-4

[42] Zheng, B., & Yao, C. (2023). Automobile Profession Responds to the Development of Automobile Intelligence. 2023 8th International Conference on Cloud Computing and Big Data Analytics, ICCCBDA 2023, 419–423. https://doi.org/10.1109/ICCCBDA56900.2023.10154651

[43] Priyadarshi, R. (2024). Energy-Efficient Routing in Wireless Sensor Networks: A Meta-heuristic and Artificial Intelligence-based Approach: A Comprehensive Review. Archives of Computational Methods in Engineering. https://doi.org/10.1007/s11831-023-10039-6

[44] Priyadarshi, R. (2024). Exploring machine learning solutions for overcoming challenges in IoT-based wireless sensor network routing: a comprehensive review. Wireless Networks. https://doi.org/10.1007/s11276-024-03697-2

[45] Qiu, Y., Ma, L., & Priyadarshi, R. (2024). Deep Learning Challenges and Prospects in Wireless Sensor Network Deployment. Archives of Computational Methods in Engineering. https://doi.org/10.1007/s11831-024-10079-6

[46] Priyadarshi, R., & Vikram, R. (2023). A Triangle-Based Localization Scheme in Wireless Multimedia Sensor Network. Wireless Personal Communications, 133(1), 525–546. https://doi.org/10.1007/s11277-023-10777-7

[47] Priyadarshi, R., & Gupta, B. (2023). 2-D coverage optimization in obstacle-based FOI in WSN using modified PSO.

Journal of Supercomputing, 79(5), 4847–4869. https://doi.org/10.1007/s11227-022-04832-6

[48] Rawat, P., Chauhan, S., & Priyadarshi, R. (2021). A Novel Heterogeneous Clustering Protocol for Lifetime Maximization of Wireless Sensor Network. Wireless Personal Communications, 117(2), 825–841. https://doi.org/10.1007/s11277-020-07898-8

[49] Priyadarshi, R., & Gupta, B. (2021). Area Coverage Optimization in Three-Dimensional Wireless Sensor Network. Wireless Personal Communications, 117(2), 843–865. https://doi.org/10.1007/s11277-020-07899-7

[50] Priyadarshi, R., & Gupta, B. (2020). Coverage area enhancement in wireless sensor network. Microsystem Technologies, 26(5), 1417–1426. https://doi.org/10.1007/s00542-019-04674-y

[51] Priyadarshi, R., Rawat, P., Nath, V., Acharya, B., & Shylashree, N. (2020). Three level heterogeneous clustering protocol for wireless sensor network. Microsystem Technologies, 26(12), 3855–3864. https://doi.org/10.1007/s00542-020-04874-x

[52] Rawat, P., Chauhan, S., & Priyadarshi, R. (2020). Energy-Efficient Clusterhead Selection Scheme in Heterogeneous Wireless Sensor Network. Journal of Circuits, Systems and Computers, 29(13), 2050204. https://doi.org/10.1142/S0218126620502047

[53] Priyadarshi, R., Gupta, B., & Anurag, A. (2020). Wireless Sensor Networks Deployment: A Result Oriented Analysis. Wireless Personal Communications, 113(2), 843–866. https://doi.org/10.1007/s11277-020-07255-9

[54] Priyadarshi, R., Gupta, B., & Anurag, A. (2020). Deployment techniques in wireless sensor networks: a survey, classification, challenges, and future research issues. Journal of Supercomputing, 76(9), 7333–7373. https://doi.org/10.1007/s11227-020-03166-5

[55] Priyadarshi, R., & Nath, V. (2019). A novel diamond–hexagon search algorithm for motion estimation. Microsystem Technologies, 25(12), 4587–4591. https://doi.org/10.1007/s00542-019-04376-5

[56] Priyadarshi, R., Rawat, P., & Nath, V. (2019). Energy dependent cluster formation in heterogeneous wireless sensor network. Microsystem Technologies, 25(6), 2313–2321. https://doi.org/10.1007/s00542-018-4116-7

[57] Priyadarshi, R., Soni, S. K., Bhadu, R., & Nath, V. (2018). Performance analysis of diamond search algorithm over full search algorithm. Microsystem Technologies, 24(6), 2529–2537. https://doi.org/10.1007/s00542-017-3625-0

[58] Priyadarshi, R., Soni, S. K., & Nath, V. (2018). Energy efficient cluster head formation in wireless sensor network. Microsystem Technologies, 24(12), 4775–4784. https://doi.org/10.1007/s00542-018-3873-7

[59] Desai, S., Kanphade, R., Priyadarshi, R., Rayudu, K. V. B. V., & Nath, V. (2023). A Novel Technique for Detecting Crop Diseases with Efficient Feature Extraction. IETE Journal of Research, 1–9. https://doi.org/10.1080/03772063.2023.2220667

[60] Priyadarshi, R., & Kumar, R. R. (2021). An Energy-Efficient LEACH Routing Protocol for Wireless Sensor Networks. In V. Nath and J. K. Mandal (Eds.), Lecture Notes in Electrical Engineering (Vol. 673, pp. 423–430). Springer Singapore. https://doi.org/10.1007/978-981-15-5546-6_35

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