FOREX Publication
Open Access | Rapid and quality publishing

International Journal of
Electrical and Electronics Research (IJEER)
Research Article | Volume 11, Issue 1 | Pages 103-111 | e-ISSN: 2347-470X

Evaluation of IIOT based Pd-MaaS using CNN with Ensemble Subspace Discriminate – for Indian Ship Building in Maritime Industry

PNV Srinivasa Rao[1*] and PVY Jayasree[2]

[1,2]Department of EECE, GITAM Institute of Technology, GITAM University, Visakhapatnam, India, pnvsrinu@yahoo.com, jpappu@gitam.edu

***Correspondence:** PNV Srinivas Rao; pnvsrinu@yahoo.com; Tel.: +91-9900-191-514

ABSTRACT- Indian shipbuilding has a long history in the maritime industry dating back to the origin of civilization. India's shipbuilding sector is primarily concentrated in its coastal regions. Due to capacity constraints and decreased shipbuilding prices in emerging nations, shipbuilding activities has changed. This has created fresh opportunities for the Indian shipbuilding industry. The prospects for the Indian shipbuilding sector are improved by rising global trade and strong need for modern boats. This study investigates the use of Predictive Maintenance as a Service on the Industrial Internet of Things (IIoT-PdMaaS). Artificial intelligence (AI) in the maritime industry has numerous major benefits, including improved decision-making analysis, automation, security, route planning, and increased efficiency. So, Pd-MaaS using IIOT (Convolution neural network (CNN) with Ensemble Boosted Tree Classifier) framework was developed in this study. This research shows 88.3% accuracy of CNN output for confusion matrix implying a positive connection with our proposed model for Indian ship building industry.

Keywords: Indian ship building, Predictive maintenance as a service, Industrial Internet of Things, Artificial Intelligence, and Convolution neural network.

ARTICLE INFORMATION
Author(s): PNV Srinivasa Rao and PVY Jayasree;
Received: 12/10/2022; **Accepted**: 20/02/2022; **Published**: 15/03/2023;
e-ISSN: 2347-470X;
Paper Id: IJEER220940;
Citation: 10.37391/IJEER.110114
Webpage-link:
https://ijeer.forexjournal.co.in/archive/volume-11/ijeer-110114.html

Crossref member
CROSSREF.ORG THE CITATION LINKING BACKBONE

Publisher's Note: FOREX Publication stays neutral with regard to Jurisdictional claims in Published maps and institutional affiliations.

1. INTRODUCTION

Industrial businesses are focusing more and more on essential services in the 21st era as they extend their product-related management, restoration, and inspection activities, in addition to technical assistance, to their customer base [1]. In this setting, shipyards nowadays perform a variety of tasks, including planning, engineering, and construction, procuring and logistics, assembly and commission, in addition to repairing, maintaining, and modernizing ships and maritime hardware, amongst others[2].With a coastline of approximately 7,517 kilometers, India is the globe's sixteenth widest maritime nation. As per the Ministry of Shipping, coastal accounts for approximately 95% of India's trading activity and 70% of its trading worth, with 12 significant harbors and 200 notified small and midlevel access points[3].

Indian shipbuilding has a long marine background that dates back to the emergence of culture in Harappa and Mohenjo-Daro. From the early 1990s, shipbuilding activity have gradually shifted from Europe to Asia due to supply restrictions in developed nations and reduced shipbuilding expenses (cheap labor) in emerging nations. At the contrary side, India's capability for shipbuilding has fallen behind the nation's financial development, competitive pressures, and human resource capability. The majority of India's shipbuilding activity took place in coastal regions including Andhra Pradesh, Cochin, Kolkata, Goa, Mumbai, and Gujarat. Possibilities have now become available for the Indian shipbuilding sector as a result[4].

Despite the worldwide economic and governmental issues, shipbuilding is still one of the longest, most significant, open, and fiercely competitive businesses in the globe. The advantages of the Indian shipbuilding sector include a plethora of coastline, close connectivity to major regional and global shipping lanes, and low labor charges, to highlight a few [5]. The outlook for the Indian shipbuilding sector was enhanced by expanding international trade and robust substitute market. The Indian shipbuilding sector has changed from being reliant on governmental contracts until the late 1990s, concentrating instead on the specialized offshore market[6].

The majority of international trade is carried out via maritime transportation, and the business's main resource of supplies for the international maritime logistics network is shipbuilding. The market is quite cutthroat and depends heavily on modern innovation. The maritime industry is evolving through a digital transformation with the introduction of self-driving and smart ships [7]. Among the four foundations of globalization, shipbuilding directly affects international trade. A conversation over how technology will change the marine sector and automated ships has been prompted by the ship firm's accelerated embrace of novel innovations[8].The sea sector is

Research Article | Volume 11, Issue 1 | Pages 103-111 | e-ISSN: 2347-470X

driven by operational effectiveness and environmental sustainability. In order to make precise replaceable elements on board, it has lately come to light that the shipbuilding industry is considering integrating additive manufacturing (AM) innovation into shipbuilding. The current situation of AM in the naval sector includes its use, architecture, and supply-chain organization[9, 10].

The connectivity of machines in a factory is what is meant by the Industrial IoT (IIoT), a sub-paradigm of the preceding one that has just arisen. The Internet of Things (IoT's) adaptable software level, which enables it relevant to a wide range of industries, is crucial in this form of communication. The IoT is a framework that links smart objects together, enabling the regulation of data and the proper operation of application operations [11]. The implementation of tasks, progress tracking, and remote sensing are just a few of the numerous features it comprises. For instance, utilizing a smart phone to check the temperature in one's home is an instance of IoT. However, utilizing the similar smart phone to check the temperature in a factory area, which has a controlled atmosphere, is therefore an instance of an IIoT application scenario [12].

According to research, it dramatically boosts business performance. IIoT extends above the internet-based functionality of typical consumer electronics and other tangible objects frequently linked to IoT. Companies now have better knowledge and management over its material assets, production procedures, and work conditions due to IIoT [13]. IIoT, which differentiates from other IoT uses in its everyday influence on better, more connected, and more effective productive processes, primarily links transportation equipment and all related commercial equipment to the internet for machine in the industry. Applications for controlling equipment, machinery, structures, or facilities are controlled by IIoT. Smart meter reading, safety systems, distant and predictive maintenance, smart factories, and asset tracking are a few instances. The industrial segment needs to gather and analyze data in order to deliver constructive information [14].

In order to place sensing devices in the industries, an IIoT system must have multiple layers of hardware and software. When coupled with a powerful computing power, this lays the groundwork for a future era of smart industries.

1.1 Research Gap

Owing to prevention and remedial administration in the marine industry, mechanical systems including plants, machines, and devices are only altered or modified at preset intervals. It may be necessary to replace marine predictive maintenance parts when they are still functioning throughout their scheduled or regular maintenance schedules, incurring extra costs. As a result, the components of the predictive maintenance system may have outlived their usefulness earlier than expected. As a consequence, the more conventional approaches to preserving marine engine systems are no longer as efficient in enhancing their toughness, security, and ease of maintenance. The voids left by conventional management could be filled by predictive maintenance. Utilizing sensing innovations or machine learning (ML) techniques like CNN in the industrial internet of things (IIoT) network, it is possible to optimize the maintenance of maritime mechanical devices.AI-based predictive maintenance utilizes a variety of data streams to determine which components needed to be changed before they fail, including data from IIoT sensors implanted in machinery, production methods, atmospheric parameters, and other streams.

1.2 Research Objective

The major targets attributed with this study's goal are listed below:

1. To review the role of Predictive Maintenance (PdM) Using Industrial Internet of Things (IIoT) and CNN for Mechanical Equipment (Ship Engine Acceleration Failure-Lifetime of engine prediction) Used into Indian Ship Building Industry. This aims to foresee potential problems and take the preventive measures before they arise.
2. To Develop a Predictive Maintenance (PdM) for Complex equipment using Multi-Distinguished-Features Sampling with Ensemble Boosted Tree Classifier Machine Learning Algorithm to detect acceleration failure in the ship.
3. To Develop a Predictive Maintenance as a service "PdMaaS" with the help of IIOT (acceleration data from sensor and cloud) and standard and enhanced ML algorithms like SVM, CNN, RF and GBM (for classification) for the Indian Shipbuilding in maritime industry. The validation of our proposed method has been discussed with various output.

1.3 Limitations of the Study

This study has potential limitations. The dataset used for the engine acceleration failure analysis of passenger ship capacity. This will help in business can use their equipment more efficiently, spend less on operations, and avoid problems before they become serious or catastrophic by calculating the amount of time before a failure is likely to occur and being able to foresee failures. It doesn't involve cargo capacity engine or any other failure analysis of engine.

1.4 Research Framework

This section includes an examination of the study's framework to help direct the research in the appropriate path. The investigation's design is centered on the facet of IIOT based Pd-MaaS using CNN with ensemble subspace discriminate for Indian shipbuilding industry, includes five sections, and the connection is described as follows.

The introduction of the study, the research gap, and the study's objective are all described in *Section 1*. *Section 2* of this research would describe the pertinent research works of literatures. In *Section 3*, a synopsis of the intended investigation is presented. The simulated results and discussion are described in *Section 4*. The report's final section, *Section 5*, elaborates in considerable detail on the findings and actions that have occurred.

2. LITERATURE REVIEW

2.1 IoT in Ship Building

Many emerging technologies like IoT, deep learning, machine learning, big data are used in the maritime and other automobile

International Journal of
Electrical and Electronics Research (IJEER)
Research Article | Volume 11, Issue 1 | Pages 103-111 | e-ISSN: 2347-470X

industries. An initiative by Hyundai Heavy Industries to integrate an IoT system in its newly constructed vessels was launched in 2015 [15]. It is concerned acquiring "smart and connected" ships that enable shipping companies to more effectively control their operations. The idea helps in equipping the ships with sensory nodes that records data while the ship is navigating. Position, sea current flow, weather, and statistics from the instruments mounted on board are examples of the kind of data. The maritime businesses can track the condition of its ships in actual period and take judgments for a better effective operation by utilizing the real-time assessment functionalities of the IoT systems.

The Internet of Things program are utilized in the More cluster (Norway) where 200 businesses in that cluster specialized are provided offshore infrastructure assistance. The operations encompasses everything from building of warships to oversee the maintenance [16]. It was chosen to combine Big Data with IoT in maritime industry. The OSV ship might incorporate a hybrid CPU architecture that can conduct description and real-time predictive maintenance study of the ship and its key machinery since the assessment of massive amounts of data demands a huge processing capability. The IoT segment of the investigation would provide the information, which would comprise RFID readers, detectors, actuator, webcams, and GPS.

2.2 Predictive Maintenance

Predictive maintenance is the significant for maritime industries for smart production in the industrial sector and technologies featuring dewatering pumps employed for docking and undocking of boats in shipbuilding might not be conceivable. In the shipbuilding of smart factory units, ML systems considered as practical tool for predictive maintenance and dewatering devices. Over the previous few decades, they significantly increased researcher’s attention. As the effort for highlighting the important pledges taken by the scientists, the researchers evaluated studies on ML methods that include Support Vector Machine for predictive maintenance and few categories of investigations relies on the ML algorithms, industrial equipment, and gadgets utilized in data collection and organization[17].

2.3 Convolution Neural Network

The deep learning algorithm used for classification of images is referred as convolutional neural network. It has the potential of extracting the special correlation as well as creation of features and information using input data for detecting patterns. CNN modeling is utilized fork task classification in predictive maintenance framework and the quality of the CNN models can be improved with extensive network with replacement of traditional rectifier linear unit activation function [18].

2.4 Significance of Research

The shipbuilding sector needs physical labor for Industrial Internet of Things-based Predictive Maintenance-as-a-Service (IIoT- PdMaaS). The majority of commodities are transported by coastal and inland streams worldwide, and this fact has always been acknowledged by all. Ship preservation is extremely important in order to maintain ships' state at a reliable organizational stage. The findings indicate that the ship's mass has the greatest impact on profitability and that continuous hull deterioration is a crucial safety factor. The secret to cutting down on operating wait time is to increase port efficiency. More significantly, the study shows that altering input variables can help in figuring out how much money is required to reach a particular level of innovation. Welders' typical hand movements were monitored and captured utilizing IMU sensing devices having nine degrees of freedom (DOF). Welders have been identified and categorized using artificial intelligence (AI) methods, such as the support vector machine (SVM) approach, depending upon their hand movements. The IIoT-PdMaaS strategy has been proposed to outperform the current approaches. Enhancing shipbuilding organizational procedures, resource administration, fuel usage, delayed duration, and predictive maintenance has been suggested using the IIoT-PdMaaS strategy.

3. METHODOLOGY

The methodology described in this research entails two steps: (a) describing an IIOT-PdMaaS approach that is appropriate for the obtained input data, and (b) developing a model that can determine whether a provided data point coincides to a nominal status taken into account during training. The most popular classifiers are Decision Trees, SVM, and CNN. *Figure 1 (b)* provides a visual illustration of the proposed methodology. A solution with a framework resembling that shown in *figure 1* ought to be attained. According to the selected method, machine data is transmitted, either raw or pre-processed, from the sensors to a centralized database in this approach. Additionally, predictive monitoring algorithms are used, and the user is shown the outcomes and alerts on simple dashboards. The main goal of the proposed methodology is Predictive Maintenance in ship engine failure analysis to prevent the delay before start.

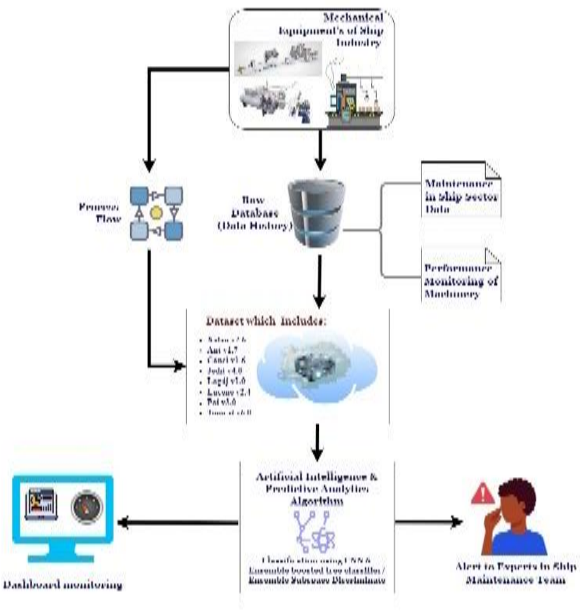

Figure 1(a): General description of an IIOT-PdMaaS approach in a ship equipment monitoring

FOREX Publication
Open Access | Rapid and quality publishing
International Journal of
Electrical and Electronics Research (IJEER)
Research Article | Volume 11, Issue 1 | Pages 103-111 | e-ISSN: 2347-470X

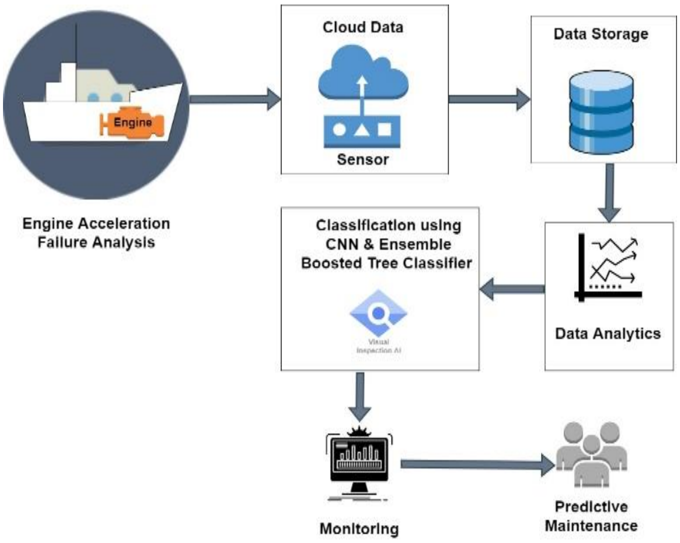

Figure 1(b): Developing a model of Ship engine failure analysis - Proposed Methodology Pd-MaaS using IIOT (CNN with Ensemble Boosted Tree Classifier)

3.1 Pd-MaaS using IIOT in Indian Ship Industry

Nowadays, the maritime sector uses IIoT technologies. Examining all of the complex systems on board a ship at once is crucial when considering IoT implantation. Its dependence on the end-user businesses that employ it stems from the fact that it is an intermediary firm. Shipbuilding investments can boost the production of steel, engineering goods, and supplies.

The technological and PdMaaS are two essential parts of the suggested framework. The suggested strategy incorporates the benefits of the IIoT, including the involvement of experts, thorough system assessment, status surveillance and data collection, execution of maintenance operations, technological support in terms of persons and equipment needed, and decision endorse mechanism. Instead of aiming for an ideal excited phase, the IIoT method tries to restore the network to a functioning state inside the operating bounds of each situation. By concentrating on their most crucial activities, the systems can increase their dependability and protection, reduce or eliminate the consequences of mistakes. To minimize maintenance costs, avoid performing maintenance that is not absolutely required or decrease the quantity that is performed [19].

3.2 Convolution Neural Network with Ensemble Boosted Tree Classifier

Figure 2 implies the flowchart of AI and predictive analytics using CNN with ensemble boosted tree classifier. This research uses a gradient boosting algorithm-trained ensemble of decision trees as the prediction model. The main contribution of the study is a strategy that breaks the trade-off between energy-area and accuracy by limiting the number of concurrently extracted features.

Most of time input dataset is not preprocessed since CNN contains three layers in feature selection so the dataset is randomly split into testing data, and training data which further classified as validation data. The features selection is done by the CNN algorithm for both training and testing data and the obtained result is a feature rank. The feature selection involves three different layers, pooling, convolution, and activation function. After then, each feature is incorporated to the ensemble model one at a time, starting with the most crucial. Finally, the data undergoes classification and prediction

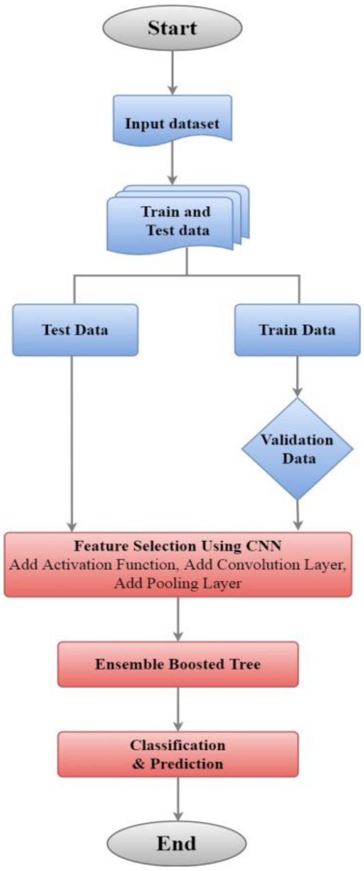

Figure 2: Flowchart for AI and Predictive Analytics - CNN with Ensemble Boosted Tree Classifier

3.2.1 CNN Architecture

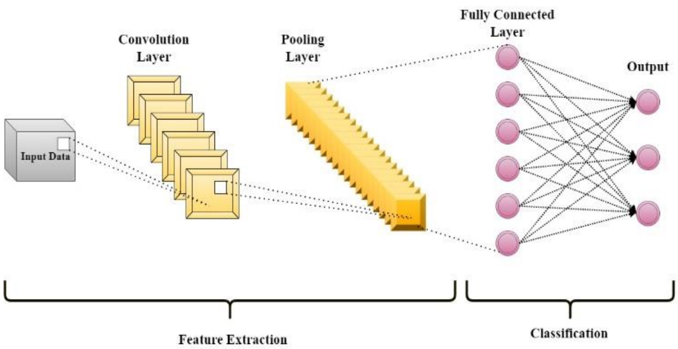

Figure 3: CNN - Architecture

In a wide range of machine learning issues, CNN has achieved outstanding outcomes. The CNN is a multilayer neural network with non-full connections that typically consists of a convolution layer (Conv), a pooling layer, and a fully-connected layer (FC). The raw data is initially convoluted on the convolution layer, which might provide many feature maps.

The polling layer then distorts the feature. A fully connected layer is then used to obtain a set of eigen vectors. The conventional CNN architecture is shown in *figure 3*. The architecture of a CNN is hierarchical. Each successive layer, xj, is calculated starting with the input signal x.

$$x_j = \rho W_j x_{j-1}$$

Wj is a linear operator in this situation, and $\rho$is nonlinearity. Wj is usually a convolution in a CNN, and $\rho$is either a rectifier max (x, 0) or sigmoid 1/1+exp(x). The operator Wj is better understood as a stacking of convolution filters. The layers are hence filter maps, and each layer can be expressed as the total of the convolutions of the layer before it.

(a) Activation Function Layer

The activation function, which can be utilized to address nonlinear problems, relates to the property of activated neurons that can be maintained and mapped out by a nonlinear function. The activation function is utilized to improve the neural network model's capacity for expression, which can give the neural network the appearance of artificial intelligence. Since ReLU activations are most frequently utilized, researchers typically represent activation layers as ReLu in network designs. Network design diagrams occasionally skip activation layers since it is presumed that activation comes just after a convolution [20].

The classification line can be achieved when y1 = 0. The multilayer perceptron based on Equation (2) may resolve the multiclass problem because the single layer perceptron cannot manage the problem of linear indivisibility.

$$y1 = \sum_{i=1}^{n} W_i x_i + b \qquad (2)$$

The equation of ReLu function is

$$f(x) = \max(0, x) \qquad (3)$$

(b) Convolution Layer

The fundamental component of a CNN is the convolution layer. The variables of the convolution layer are made up of a set of K learnable filters, or "kernels," each of which has a width and a height and is almost usually square. These filters cover the entire depth of the volume despite being modest (in respect of its spatial characteristics) [19]. The outcome of the preceding layer convolution throughout the forward propagation phase due to the convolution kernel, and the result of this layer may be calculated using the accompanying equations:

$$u_j^l = \sum_{i \in M_j} x_j^{l-1} k_{ij}^l b_j^l \qquad (4)$$

$$x_i^j = f(u_j^l) \qquad (5)$$

in which x_j^{l-1} is indeed the yield feature map of the i channel in the previous layer, $k_{ij}^l$is the convolution kernel matrix, the output feature map of the previous layer can be used to compute the net output $u_j^l$of the i layer, and the activation function f can be used to obtain the output x_i^j of the i layer and the j channel.

(c) Pooling Layer

Another crucial component of a CNN is the pooling layer, which is utilized to further reduce the spatial dimensionality of a convolution layer's result, reduce the network's computation cost and variable count, and manage overfitting. In the following layer, the pooling layer unifies the outcome of neuron clusters in the sub-regions of a convolution layer into a single neuron. Max pooling, Average pooling, and L2 pooling are the three most popular kinds of pooling. Usually, CNNs utilize a 2×2-dimensional kernel with a 2 stride along the input's spatial dimensions in the scenario of max pooling. Stride is the separation between two successive filter points in the input layer, measured in both width and height [21].

$$H^{l+1} = \frac{H^l}{H}, W^{l+1} = \frac{W^l}{W}, D^{l+1} = D^l \qquad (6)$$

A pooling layer works individually on xlslice by slice, or channel by channel. The matrix with Hl× Wl elements is spatially separated into $H^{l+1} \times W^{l+1}$ subspaces, each of which is H × W in size, in each slice.

3.2.2 Ensemble Boosted Tree Classifier

Figure 4 presents the illustration of boosted ensemble learning. An approach known as "boosted ensemble" aims to create a strong classifier out of a large variety of weak classifiers. It helps any learning system become more accurate. It is accomplished by utilizing weak models in series to develop a model. Initially, a model is created using the training set of data. The 2nd model is then created in an effort to fix the previous model's flaws. Models are added in this manner until either the entire training data set is successfully forecasted or the optimum set of models is loaded. It helps transform "weak" learning algorithms into comparatively "strong" learning algorithms by outperforming them just marginally. The basic learning algorithm creates a novel weak prediction rule, and after numerous iterations, the boosting algorithm merges each of the supposedly weak rules into one prediction rule, which will produce a prediction rule with a greater accuracy than any one of the separate weak rules [21, 30].

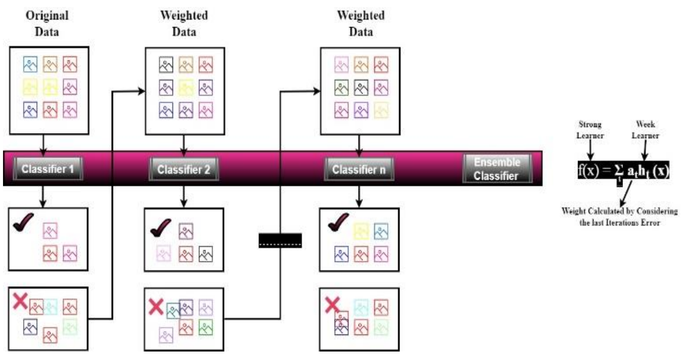

Figure 4: Boosted Ensemble Learning

Using x as its input features vector, a boosted classifier's result takes on the cumulative structure of

$$H(x) = \sum_{t} \alpha_t h_t(x) \qquad (7)$$

Where "α_t" denotes how much weight must be placed on $h_t(x)$. Assume that Ti,i ∈1, 2…, k are the representations of k trees. Considering that Ti is the overall amount of time related to the longest route in Ti, we choose the ideal update time as topt = min {t1, t2, · · ·,tk}. This ensures that at minimum one tree will be finished throughout this time, and a fresh choice is made for each topt. Next, we determine each tree's average decision value:

$$D_{T_i} = \frac{1}{N_i}\sum_{j=1}^{N_i} r_j \tag{8}$$

Wherein Ni is the total number of cycles that have been performed over topt and r1, r2, …., rNi are the equivalent outcomes (i.e., leaf values) of Ti. In a boosting classifier, the final determination must be made by averaging the responses from all trees. Seizures are categorized as positive and non-seizures as negative responses. The system's ultimate output is thus updated as follows:

$$D_{final} = \sum_{i=1}^{k} D_{T_i} \tag{9}$$

4. RESULTS

The findings from the aforementioned case studies are presented and discussed in this section. The output of the method for various input metrics is shown for all study outcomes. *Figure 5* implies the prediction graph of the training model. Where x and y are coordinates of training model and CNN's confidence score is represented by color.

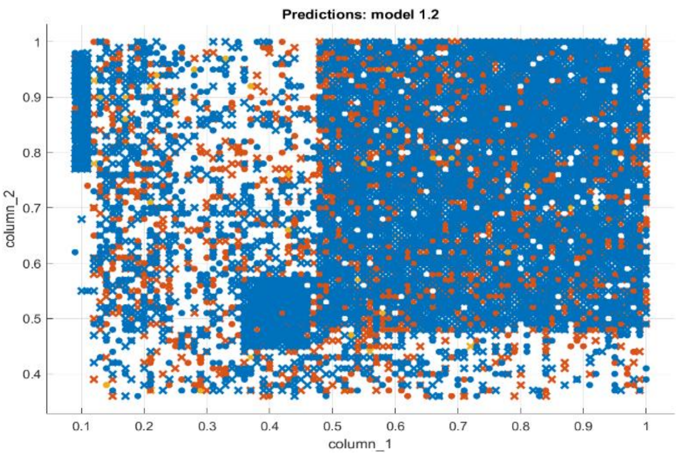

Figure 5: Training Model

From *figure 5* it is clear that data set of training model is oriented all over the space. These distributions all demonstrate the algorithm's extensive line coverage. Maximum (blue and red dots) and minimum (yellow dots) points are observed.

ROC Curve

Figure 6 shows the ROC (Receiver Operating Characteristic Curve) of our model with ensemble classifier and AUC (area under the ROC curve). The ROC curve depicts a classification model's performance at all classification thresholds and is shown between 2 factors [31]. They are False Positive and True Positive Rates. The AUC is a summary of model predictive accuracy. Typically, if AUC is equal to 0.5 while the ROC curve represents random chance, and it is equal to 1.0 for perfect accuracy. The calculated AUC is occasionally less than 0.5, implying that the test performs poorer than chance

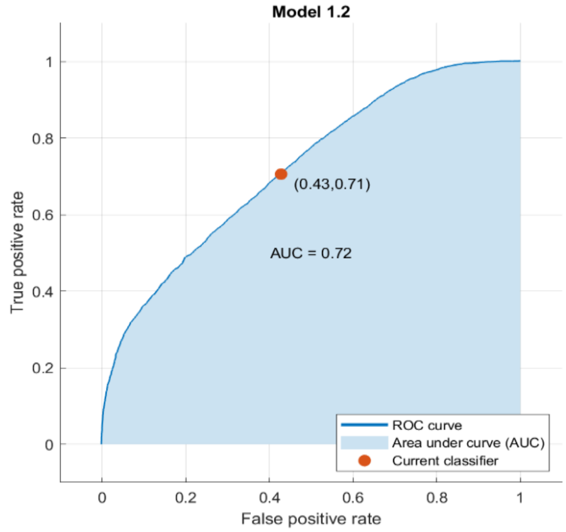

Figure 6: ROC Curve of the model

This ROC curve clearly indicates that AUC is 0.72 which is more than random chance proving that there is a significant chance of accuracy. The (true positive rate and false positive rate) of classifier is (0.43, 0.71) at threshold 1. *Figure 7* implies the correlation value.

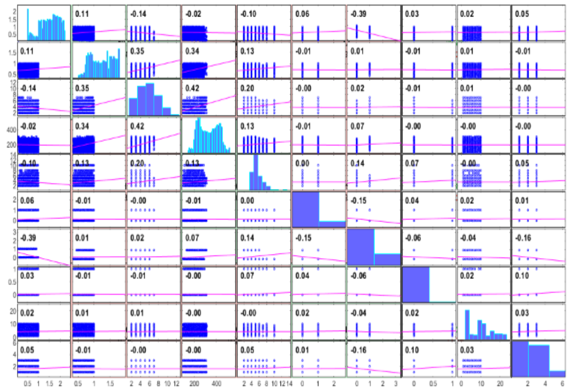

Figure 7: Correlation value

According to the results the training model off predictive maintenance clearly indicates the AUC of 0.72 in ROC curve and the correlation value choose that true positive rate is 0.43 and false positive rate 0.71. That's the results show that predictive maintenance uses industrial Internet of Things and CNN for detection of failure in ship engine and engine prediction for lifetime can be used in Indian shipbuilding industry to provide solutions and preventive measures before the problem occurs. The predictive maintenance uses multi distinguished feature sampling with ensemble a boosted tree classifier for detection of acceleration failures or starting problems in the ship.

Research Article | Volume 11, Issue 1 | Pages 103-111 | e-ISSN: 2347-470X

5. DISCUSSION AND VALIDATION

The input parameters of the CNN for the proposed method are shown in *table 1*. The confusion matrix for the output of CNN is shown in *table 2* and *figure 8*. One of the main metrics utilized in CNN designs for the classification phase is the confusion matrix [32, 33].

Table 1: Structural parameters of the CNN for the matrix of input parameters 5x5

Layers	Operation	Dimension	Kernal
Input Layer	Input	5 X 5	2
Convolution	Convolution	5 X 5	9
Pooling	Average	5 X 5	2
Convolution	Convolution	5 X 5	15
Pooling	Average	5 X 5	2
Convolution	Convolution	5 X 5	21
Pooling	Average	5 X 5	2
Classification	Ensemble	5 X 5	2

Table 2: Confusion matrix

Parameters	Performance of GAN in %
Accuracy	99.7253%
Sensitivity	100%
Specificity	100%
Error rate	0.0026
Positive predictive value	1.0000
Negative predictive value	0.9998
Positive likelihood	NaN
Negative likelihood	0.0016

The confusion matrix output of CNN is quite impressive we obtain 88.3% accuracy. With sensitivity of 90.5%, specificity of 88.2%, positive predictive of 0.9% and positive likelihood of 7.8% are also observed. We successfully predicted the performance rate with which the CNN algorithm learns the model behavior from the dataset when the model is being trained and tested. *Table 3* shows the validation our proposed work.

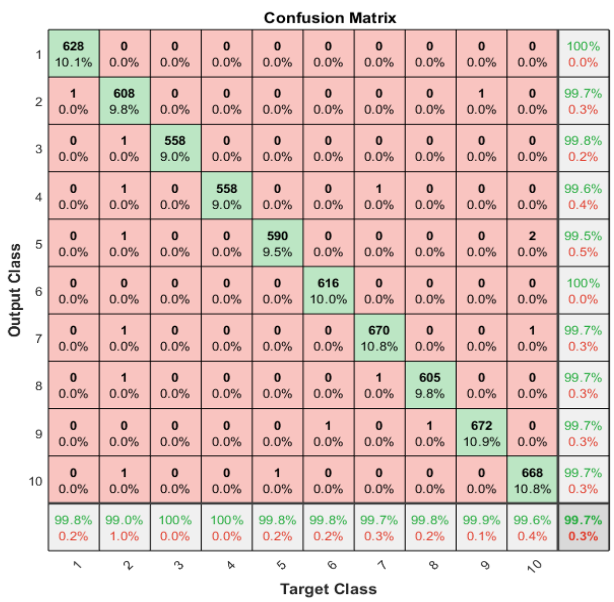

Figure 8: Confusion matrix

Table 3: Validation of our proposed method with other algorithm and applications

Deep Learning Algorithm	Dataset	Application	Accuracy	References
CNN	Sensory Data	Recognizing Employee Activity	98%	[23]
CNN	Bearing Data	Monitoring and Diagnosis in the Manufacturing	90%	[24]
AE	FEMTO-ST – IEEE Data	Bearing's remaining usable life forecast	93%	[25]
CNN	Sensory Data	System for Manufacturing Inspection	85%	[26]
AE	Samples of Process Data	Fault classifications	90.2%	[27]
LSTM	Sensor information collected form 33 sensors placed on power station pump	Analysis of Industrial IoT Technology	90%	[28]
DCNN	Obtained information from wildlife television	Surveillance Applications	99.53%	[29]
Proposed Methodology	IoT Sensor Data from Indian Ship Engine Data (Acceleration Failure)	Indian Ship Predictive Maintenance (Pd-MaaS)	99.7253%	

6. CONCLUSION

The ensemble boosted classifier is one of the new techniques provided in this research for choosing the appropriate maintenance sequence in the maritime industry. India needs to concentrate on a number of businesses in order to flourish, according to research on the global and Indian shipbuilding sectors. Proactive and predictive maintenance can boost total reliability and accessibility in addition to saving time and money. This paper has potential limitation which is having only passenger ship acceleration data, in future can have cargo ship capacity as well. In our network of interdependent shipping and port operators, Pd-MaaS comprised service suppliers for ports and consolidation/distribution. As they connect and characterize multiple sectors, organizational and management events must be studied in relation to this feature. Issues with transportation are resolved with CNN. They can use shipping CNN to apply complex AI algorithms to a problem like connecting transporters and shippers. This study concentrated on the service phase of a smart factory instead of the production stage for a vessel repair depot. In this study, we optimized the framework we used to train our data to an accuracy of about 88.3%. The proposed methodology that uses IoT sensor from data of Indian ship engine for detecting acceleration failure by using Indian ship predictive maintenance as a service provides accuracy of 99.7253%. The obtained result helps in predicting the fault at early stage before it occurs. The detection of acceleration problems helps to maintain the ship engine for lifetime.

7. FUTURE WORKS

Finally, model training with a larger, more comprehensive data is a future research step.

In addition, it is suggested that a decision support system be created and put into use to provide recommendations for choosing the optimum maintenance procedures. A more reliable model will be produced by also taking into account the utilization of vibration in addition to performance measures.

Further, the optimization techniques can be used with hybrid techniques such as combining algorithm can be used to get more optimum result.

8. ACKNOWLEDGMENTS

We thank the management of GITAM University for all the support and encouragement rendered in this project. We also extend our thanks to the Vice Chancellor and Registrar of GITAM University for providing the required facilities for carrying out this work. Our sincere thanks are also due to the Principal of GITAM Institute of Technology, Head of the Department of E.E.C.E and its staff for their kind support.

REFERENCES

[1] Herterich, M. M., Uebernickel, F., & Brenner, W. (2015). The impact of cyber-physical systems on industrial services in manufacturing. Procedia Cirp, 30, 323-328.

[2] Mascaraque-Ramírez, C., & Para-González, L. (2022). Can the six dimensions of Marketing Promotion enhance performance in the international shipbuilding industry? Proceedings of the Institution of Mechanical Engineers, Part M: Journal of Engineering for the Maritime Environment, 236(1), 245-256.

[3] Mourougane, A. (2020). Present Scenario of Ship Building Industry in Indian. Center for Development Economic, 6(06), 29-38.

[4] Thangam, K. M., & Sureshkumar, D. (2015). Competitiveness of Indian ship building industry. International Journal of Innovative Research & Development, 4(7), 18-25.

[5] Jaison, M. (2021). TOWARDS GREATER SHIPBUILDING SUPPLY CHAIN SURPLUS IN INDIA–A REVIEW. Industrial Engineering Journal (ISSN-0970-2555), 14(1), 5-14.

[6] Sender, J., Illgen, B., Klink, S., & Flügge, W. (2021). Integration of learning effects in the design of shipbuilding networks. Procedia CIRP, 100, 103-108.

[7] Shahbakhsh, M., Emad, G. R., & Cahoon, S. (2022). Industrial revolutions and transition of the maritime industry: The case of Seafarer's role in autonomous shipping. The Asian Journal of Shipping and Logistics, 38(1), 10-18.

[8] Ichimura, Y., Dalaklis, D., Kitada, M., & Christodoulou, A. (2022). Shipping in the era of digitalization: Mapping the future strategic plans of major maritime commercial actors. Digital Business, 2(1), 100022.

[9] Theodoropoulos, P., Spandonidis, C. C., & Fassois, S. (2022). Use of Convolutional Neural Networks for vessel performance optimization and safety enhancement. Ocean Engineering, 248, 110771.

[10] Taşdemir, A., & Nohut, S. (2021). An overview of wire arc additive manufacturing (WAAM) in shipbuilding industry. Ships and Offshore Structures, 16(7), 797-814.

[11] Kiel, D., Arnold, C., & Voigt, K. I. (2017). The influence of the Industrial Internet of Things on business models of established manufacturing companies–A business level perspective. Technovation, 68, 4-19.

[12] Kiran, S., & Sriramoju, S. B. (2018). A Study on the Applications of IOT. Indian Journal of Public Health Research & Development, 9(11).

[13] Bi, Z., Da Xu, L., & Wang, C. (2014). Internet of things for enterprise systems of modern manufacturing. IEEE Transactions on industrial informatics, 10(2), 1537-1546.

[14] Schneider, S. (2017). The industrial internet of things (iiot) applications and taxonomy. Internet of Things and Data Analytics Handbook, 41-81.

[15] Kim, G. S., & Lee, Y. H. (2021). Transformation towards a smart maintenance factory: The case of a vessel maintenance depot. Machines, 9(11), 267.

[16] Wang, K., Yan, X., Yuan, Y., & Li, F. (2016). Real-time optimization of ship energy efficiency based on the prediction technology of working condition. Transportation Research Part D: Transport and Environment, 46, 81-93.

[17] Ariany, Z., Pitana, T., & Vanany, I. (2022). Review of the Risk Assessment Methods for Shipbuilding in Indonesia. In IOP Conference Series: Earth and Environmental Science (Vol. 972, No. 1, p. 012056). IOP Publishing.

[18] Kiangala, K. S., & Wang, Z. (2020). An effective predictive maintenance framework for conveyor motors using dual time-series imaging and convolutional neural network in an industry 4.0 environment. Ieee Access, 8, 121033-121049.

[19] Hafeez, T., Xu, L., & Mcardle, G. (2021). Edge intelligence for data handling and predictive maintenance in IIOT. IEEE Access, 9, 49355-49371.

[20] Wang, Y., Li, Y., Song, Y., & Rong, X. (2020). The influence of the activation function in a convolution neural network model of facial expression recognition. Applied Sciences, 10(5), 1897.

[21] Wu, J. (2017). Introduction to convolutional neural networks. National Key Lab for Novel Software Technology. Nanjing University. China, 5(23), 495.

[22] Shoaran, M., Haghi, B. A., Taghavi, M., Farivar, M., & Emami-Neyestanak, A. (2018). Energy-efficient classification for resource-constrained biomedical applications. IEEE Journal on Emerging and Selected Topics in Circuits and Systems, 8(4), 693-707.

[23] Tao, W., Lai, Z. H., Leu, M. C., & Yin, Z. (2018). Worker activity recognition in smart manufacturing using IMU and sEMG signals with convolutional neural networks. Procedia Manufacturing, 26, 1159-1166.

[24] Yuan, Y., Ma, G., Cheng, C., Zhou, B., Zhao, H., Zhang, H. T., & Ding, H. (2018). Artificial intelligent diagnosis and monitoring in manufacturing. arXiv preprint arXiv:1901.02057.

[25] Ren, L., Sun, Y., Cui, J., & Zhang, L. (2018). Bearing remaining useful life prediction based on deep autoencoder and deep neural networks. Journal of Manufacturing Systems, 48, 71-77.

[26] Li, L., Ota, K., & Dong, M. (2018). Deep learning for smart industry: Efficient manufacture inspection system with fog computing. IEEE Transactions on Industrial Informatics, 14(10), 4665-4673.

[27] Jiang, L., Ge, Z., & Song, Z. (2017). Semi-supervised fault classification based on dynamic Sparse Stacked auto-encoders model. Chemometrics and Intelligent Laboratory Systems, 168, 72-83.

[28] Zhang, W., Guo, W., Liu, X., Liu, Y., Zhou, J., Li, B., ... & Yang, S. (2018). LSTM-based analysis of industrial IoT equipment. IEEE Access, 6, 23551-23560.

[29] Krishnaveni, P., & Sutha, J. (2020). Novel deep learning framework for broadcasting abnormal events obtained from surveillance applications. Journal of Ambient Intelligence and Humanized Computing, 1-15.

[30] Bharathi, S., & Venkatesan, P. (2022). Enhanced Classification of Faults of Photovoltaic Module Through Generative Adversarial Network. IJEER, 10(3), 579-584.

[31] Femy, P. H., & Jayakumar, J. (2021). A Review on the Feasibility of Deployment of Renewable Energy Sources for Electric Vehicles under Smart Grid Environment. IJEER, 9(3), 57-65.

International Journal of
Electrical and Electronics Research (IJEER)
Research Article | Volume 11, Issue 1 | Pages 103-111 | e-ISSN: 2347-470X

[32] Kulkarni, S., & Thosar, A. (2022). Performance Analysis of Fault Tolerant Operation of PMSM using Direct Torque Control and Fuzzy Logic Control. IJEER, 10(2), 297-307.

[33] Ramanna, D., & Ganesan, V. (2022). Low-Power VLSI Implementation of Novel Hybrid Adaptive Variable-Rate and Recursive Systematic Convolutional Encoder for Resource Constrained Wireless Communication Systems. IJEER, 10(3), 523-528.Fröhlich, B. and Plate, J. 2013. The cubic mouse: a new device for three-dimensional input. In Proceedings of the SIGCHI Conference on Human Factors in Computing Systems.