e-ISSN: 2582-5208
International Research Journal of Modernization in Engineering Technology and Science
(Peer-Reviewed, Open Access, Fully Refereed International Journal)
Volume:04/Issue:11/November-2022 Impact Factor- 6.752 www.irjmets.com

PREDICTIVE MODELLING FOR ENVIRONMENTAL TELEMETRY DATA AND DAMAGE PREDICTION

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DOI : https://www.doi.org/10.56726/IRJMETS31545

ABSTRACT

Big data is being produced by the IoT more and more. Realizing this hinges on being able to extract relevant information from huge data. Big data may be utilized to optimize processes. This may be done using neural networks and machine learning, which also makes it possible to create intelligent apps that exploit this data. Sensory boxes were used to collect data from rooms, and many LSTM-based neural networks were employed to forecast the sensor values in the future. Calculations were made to determine the absolute mean error and standard deviation of the forecasts. A standard deviation-adjusted absolute mean figure was used to gauge how long it took to create a forecast. The performance and prediction accuracy of the LSTM models were then assessed. Smart healthcare platforms can continually monitor the health and activities of patients and the elderly, as well as the security and safety of the environment, with the use of environmental sensors and wearable technology. When combined with a person's medical history, this constant flow of data can provide tailored diagnosis and treatment and automate crucial duties like medical data archiving and assessing the efficacy of medical therapies. Recent developments in big data processing and artificial intelligence (AI) technology have made it possible to construct extremely dependable, precise, and strong infrastructures for data capture and processing. The main aim of the author is to predict the damage happening in the sensors that are used to detect the environmental data and also the damage prediction of the sensors using random forest as the technique for the prediction.

Keywords: Analysis, Machine Learning, LSTM, Artificial Intelligence, Predictive Modelling, Environmental Telemetry.

I. INTRODUCTION

A computer model is used to forecast the cumulative galvanic corrosion damage by considering the history of environmental exposure as determined by corrosion sensors. In order to provide accurate forecasts of cumulative corrosion damage, it is essential to understand the environmental exposure that an aircraft has experienced over the course of its lifetime. Comparing utilizing historical atmospheric data records with dynamic environmental monitoring using sensor technologies, a major benefit is offered[2]. Through statistical manipulation of the sensor data, time-of-wetness (TOW) estimates are created such that distinct environmental characterizations (WET, SEMI-WET, and DRY) of the whole exposure history may be obtained. To forecast galvanic stress and metal loss, computational models need data on electrolyte conductivity, film thickness, and polarization characteristics[4]. The cumulative corrosion damage for a certain operational period may be anticipated by integrating TWO data with electrolyte parameters for each of the discrete environmental exposure circumstances and utilizing corrosion rates from computational models. Using actual environmental exposure data gathered on board a navy vessel, a demonstration of this novel technique (corrosion Service Life Model) is provided. This prediction model may also take into account the consequences of pitting and crevice corrosion. The method may be used on a variety of constructions exposed to atmospheric corrosion, not just airplanes[1].The framework is based on the hybrid SHM technique and combines a machine learning algorithm in a supervised learning approach with the usage of a calibrated numerical finite element (FE) model to create data from various structural state states under varied environmental circumstances[5]. To gather data from a local and global sensor setup on a genuine bridge under various structural state circumstances, a thorough experimental benchmark research is conducted. Structural damage is inflicted based on a thorough analysis of typical forms of steel bridge damage documented in the literature[6]. The machine learning model is then evaluated using the experimental data. By independently analyzing various scenarios while taking into account natural frequencies, mode shapes, and mode shape derivatives, it is shown that meaningful structural damage may be produced based on the hybrid SHM framework. As a result, the work reported in this paper makes a substantial contribution to developing SHM systems that may be used with steel bridges that are already in existence[8]. Any bridge structure that can have meaningful structural damage simulated and experimental data collected can use the suggested framework. Early damage detection is the goal of structural health monitoring (SHM) systems, which help prevent the failure of structural systems or components[10]. For bridges, SHM systems may be utilized to improve inspection effectiveness, reduce unscheduled downtime, and maximize life-safety advantages through continuous monitoring. Worldwide, the large number of bridges in need of lifetime extensions is a serious worry, and operational demands including traffic loads, speed, and intensity are rising[12]. The most frequent causes of damage for steel and composite bridges are caused by fatigue in or below the bridge deck. Additionally, the structural reaction is impacted by the operating and environmental variables' unpredictability, which might conceal damage-related changes. The first step is to create, parameterize, and validate a numerical model. It might be difficult to parameterize the numerical model, especially when choosing the parameters related to damage. Second, because of modeling errors such model simplifications and uncertainty in the structural parameters, there are inherent uncertainties in the application of numerical models for damage identification[13]. Third, the structural response might be affected by operational and environmental variability, which can hide damage-related changes and create uncertainty throughout the model updating process. In addition, the model update procedure is reliant on the modal characteristics among other measured outputs. The accuracy and weighting of these outputs in the model update, as well as the sensitivity of the damage detection findings to the quantity of observed outputs, are constraints. A sensor is a precise device that monitors and reacts to a variety of environmental conditions, such as light, heat, motion, moisture, pressure, etc., and translates those conditions into a human-readable display that may be shown locally or sent over a network for additional processing. Sensors can be used to identify the nascent and unsolvable issues that arise as a result of landslides. Sensors play a crucial role in helping communities, both alive and inanimate, escape ominous circumstances that arise in the environment. Dealing with the destruction of flora and wildlife due to landslides makes it tough to put an end to them[14]. The lives of both animal and inanimate objects in the environment are put in a perilous condition by landslides. Because of the natural calamity, it is challenging to stop the landslide. The tranquil rhythm of the beloved surroundings is disturbed. Sensors adorn environmental signals with vibrant visuals and translate them into displays that people can read. Due to its high sensitivity, low power consumption, linearity, and reduced noise detection and disturbance, sensors are regarded as vital instruments. The rapid speed of life is made easier by sensors, which identify hazardous environmental activities. Settlement problems experienced by both living things and inanimate objects can be lessened. Therefore, we may conclude that wireless sensor networks are the most helpful and play a crucial part in environmental concerns[15].

II. LITERATURE OVERVIEW

The landslide forecasting system makes use of the fact that landslides in the hills can be continuously monitored by sensors that can operate in real time[16]. The use of GPS is seen to be crucial for a variety of scientific applications. These sensors improve accuracy, productivity, monitoring capabilities, quickly, and economically relative to the size of the pulchritudinous hills, and they are frequently superior to traditional geodetic survey techniques[17]. Therefore, it is advised to develop a careful attitude toward theft in order to mitigate its long-term effects in cases where the environment unexpectedly calls its own descendants. A brief lengthily planned contortion materializes, causing a shocking delay of many orders of magnitude in everyone's pulchritudinous way of existence. The initial step was to identify the best and most popular machine learning algorithm for forecasting sensor data. The discovery of LSTM networks, which are widely known and effective at processing time series data, marked the achievement of this milestone[18]. Since only time series data were employed in this thesis, LSTM was a wise choice. The creation of a system, scenario, and measurement setup for forecasting future values was the second milestone. When the smart building scenario was selected, this was accomplished. The sensing boxes and the Grafana server enabled the system and measurement configuration to be completed. Implementing the selected ML algorithm in the selected scenario was the third milestone. The LSTM network was implemented, trained on the sensor readings from the Grafana server, and used to

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anticipate this goal[19]. The fourth milestone required measuring the NNs' performance, which was done by timing the production of predicted values and contrasting them with the corresponding observed values. The fourth milestone was likewise reached by computing the mean error and the Stdev for the errors. The evaluation of the anticipated values and the selected ML approach in terms of implementation challenges, implementation constraints, and prediction accuracy comprised the fifth and final milestone. This thesis's scientific objective was to evaluate NNs' suitability for sensor value prediction for environmental sensors based on the prediction's consistency and accuracy. The finding for this objective is that NNs are excellent for forecasting sensor readings. All of the models developed for this thesis can be used in smart building applications, however multi-step models are more valuable since they can forecast longer time periods with, on average, excellent accuracy and consistency. The forecasts include some mistakes, but they are nevertheless helpful when less precise predictions are sufficient[20].

III. METHODOLOGY

a. Dataset

Here in the dataset we have Ecological telemetry information from a progression of (3) IoT gadgets. Time stamp of perusing is referenced with 405k substantial sections, each gadget has a particular gadget name. A pie diagram is likewise given in which it shows light recognized rate as 72.2% and non light distinguished as 27.8%.

	ts	device	co	humidity	light	lpg	motion	smoke	temp
0	1.594512e+09	b8:27:eb:bf:9d:51	0.004956	51.000000	False	0.007651	False	0.020411	22.700000
1	1.594512e+09	00:0f:00:70:91:0a	0.002840	76.000000	False	0.005114	False	0.013275	19.700001
2	1.594512e+09	b8:27:eb:bf:9d:51	0.004976	50.900000	False	0.007673	False	0.020475	22.600000
3	1.594512e+09	1c:bf:ce:15:ec:4d	0.004403	76.800003	True	0.007023	False	0.018628	27.000000
4	1.594512e+09	b8:27:eb:bf:9d:51	0.004967	50.900000	False	0.007664	False	0.020448	22.600000

Figure 1: Dataset Overview

b. Feature Visualisation'

Here in figure 2 we can see a visual diagram of 3 contrast gadgets with novel id and their time taken to recognize which different gadgets are thought about. Device_C2 has the most noteworthy identification time with 0.014 and the quickest and least time is likewise taken by Device_C2 which is 0.002.Here in figure 3 we can see a plot diagram addressing AI model among smoke and carbon Monoxide which has a uniform slant and time, gadget, mugginess, smoke and temperature are utilized as an informational index for examination, and the scale set on both hub is identical to 0.002 on one unit.Also in figure 4 which features are important for the model can be seen.

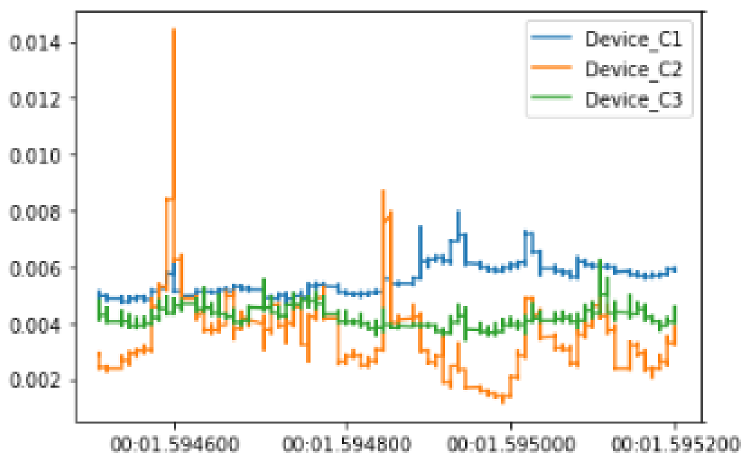

Figure 2: Different devices timing

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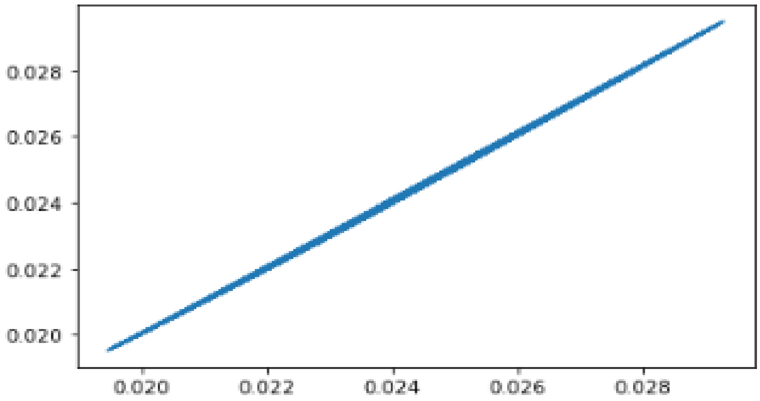

Figure 3: AI plot diagram

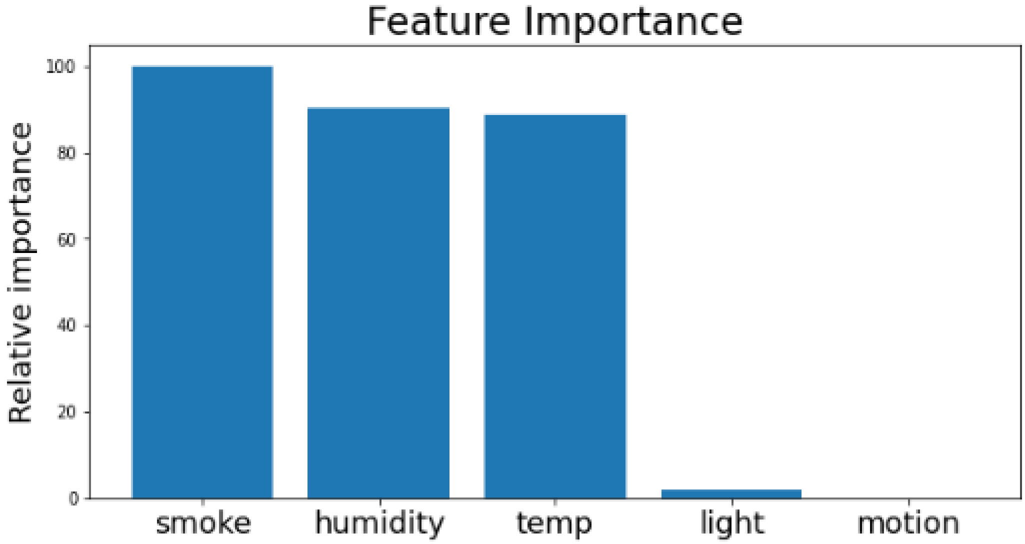

Figure 4: Feature Importance

c. Model Architecture

IoT gadgets are the nonstandard figuring gadgets that interface remotely to an organization and can communicate information, like the numerous gadgets on the web of things (IoT). IoT includes broadening web availability past standard gadgets, like work areas, PCs, cell phones and tablets, to any scope of customarily "idiotic" or non-web empowered actual gadgets and regular articles. Inserted with innovation, these gadgets can impart and interface over the web. They can likewise be remotely observed and controlled. Bunching is the undertaking of separating the populace or data of interest into various gatherings with the end goal that data of interest in similar gatherings are more like different data of interest in a similar gathering and unlike the data of interest in different gatherings. It is essentially an assortment of articles based on comparability and divergence between them. Random forest is a well known AI calculation that has a place with the directed learning procedure. It very well may be utilized for both Order and Relapse issues in ML. It depends on the idea of outfit realizing, which is a course of joining different classifiers to take care of a mind boggling issue and to work on the exhibition of the model. As the name recommends, "Irregular Woodland is a classifier that contains various choice trees on different subsets of the given dataset and takes the normal to work on the prescient precision of that dataset." Rather than depending on one choice tree, the irregular backwoods takes the expectation from each tree and in view of the greater part votes of forecasts, and it predicts the last result.

In figure 5 a confusion matrix can be seen which helps where the model lacks and can be trained properly to increase the accuracy.

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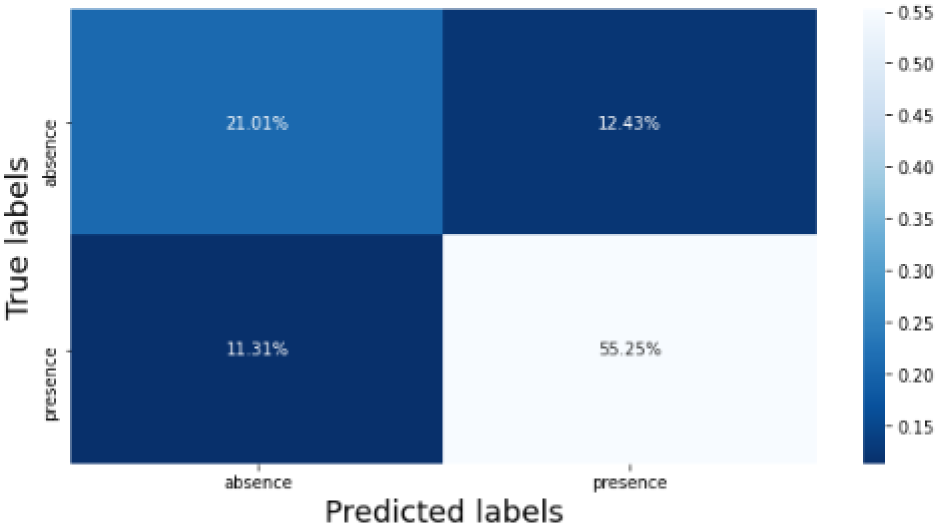

Figure 5: Confusion Matrix

IV. CONCLUSION

The prediction of the faulty pieces out in the sensor is necessary, which enable us to get the problem occurring in the data that is provided by the sensors. Hence, the techniques used by the authors which is random forest provides about 92 percent prediction accuracy for measuring the problem in the sensor and correct it to get the best results.

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e-ISSN: 2582-5208

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