Analysing ML, DL Approaches for Real-Time Maintenance Forecasting in Industrial Scenarios

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Abstract: Predictive maintenance became increasingly crucial in large machines like extruder machines to ensure optimal performance & prevent costly downtimes. Monitoring temperature is particularly critical in extruder machines as it directly impacts product quality. To address this, real-time data from a plastic extruder machine equipped with four temperature sensors taken into account to ensure precise temperature control for high-quality output. The study analysed a dataset comprising 19679 rows of data, stored in an Excel sheet, using a range of ML and DL algorithms. Primary focus was evaluating performance of these algorithms in predictive maintenance tasks. Among the algorithms tested, the Probabilistic Neural Network, a type of ML algorithm, demonstrated promising results. PNN achieved accuracy of 99.70%. PNN showed several advantages when compared to other popular algorithms such as Backpropagation Neural Network, Convolutional Neural Network, Support Vector Machine, Long Short Term Memory, and Bidirectional LSTM. PNN requires minimal parameter tuning compared to complex algorithms like LSTM & Bi-LSTM, simplifying implementation process. In conclusion, the research highlights the effectiveness of the PNN algorithm in predictive maintenance tasks for extruder machines based on temperature sensor data. Its performance and simplicity makes it a promising choice for real-time maintenance prediction, offering potential cost savings and operational efficiency improvements in industrial settings.

1 INTRODUCTION

Maintenance management is one of the pivotal operations in each industry since it enables better performance and flexibility of equipment. Operational Maintenance (OM) practices that follow quick and inexpensive predetermined approaches to problems based on analysis done over time often fails to capture the situations that occur at the time leading to un- scheduled downtimes and increased costs. Also, the real time needs maintenance primarily emphasized in periods where breakdowns in equipment would cost delays in production or great losses.

In contrast with others, through supporting day-to-day operation this also focuses ensuring that all existing issues related to equipment are repaired before they worsen as in most situations where there is a breakdown. Maintenance, be it corrective, preventive or real-time involves the identification of the presence of a defect followed by the necessary repair actions. Real-time maintenance management consists of data analysing, equipment monitoring, and fast responding to all performance-related issues emerging during the process.

Such alterations, however, cannot be made if only periodic maintenance management systems are utilized whereby a palate of issues is waited for until they arise then rectified. But true to its name 'real' implies that effects of cutting back on resources at the expense of safety of a facility or assets is minimized through active restraint on damage potentially caused by the cutting back. A strong predictive maintenance

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mechanism that cans add-on temperature trends, diagnosis maintenance needs is the way to go.

The Probabilistic Neural Network (PNN) is a type of machine learning algorithm known for its effectiveness in handling noisy data and robustness against outliers. Its architecture allows for efficient processing of large datasets, making it suitable for real-time maintenance predictions. PNN requires minimal parameter tuning compared to more complex algorithms, simplifying the implementation process. This makes PNN an attractive option for industries seeking to enhance their maintenance strategies without incurring significant complexity. In this paper, we explore the use of PNN for predictive maintenance by analysing a dataset of temperature readings from a plastic extruder machine. By comparing PNN's performance with other popular algorithms such as Backpropagation Neural Network (BPNN), Convolutional Neural Network (CNN), Support Vector Machine (SVM), Long Short Term Memory (LSTM), and Bidirectional LSTM (Bi-LSTM), we demonstrate the advantages of using PNN in this specific application. Our findings highlight PNN's potential to improve maintenance prediction accuracy, ultimately contributing to cost savings and operational efficiency in industrial settings.

2 LITERATURE SURVEY

Predictive Maintenance (PdM) plays an important role in the digital era of Industry 4.0. Researchers has performed an extensive research devoted to PdM. Research highlighted its potential benefits and effective implementation strategies.

The study enhanced power transformer fault diagnosis using an improved Probabilistic Neural Network (PNN) model optimized with an enhanced Gravitational Search Algorithm (GSA) featuring chaos sequences (Wang, 2024). The study introduced a parallel neural network (PNN) architecture for accurate remaining useful life (RUL) estimation of bearings, integrating 1D time series and 2D image-based features for enhanced prediction efficiency (Niazi, 2023). This study explored predictive maintenance for lead-acid batteries in heavy vehicles using LSTM neural networks and RSF models with sparse, irregular operational data (Sergii, 2023). This study integrated AI- driven monitoring algorithm achieved high accuracy (0.97 with XG-Boost), enhancing equipment reliability, reducing downtime, and improving operational efficiency (Chen, 2023). This study enhanced predictive maintenance in Industry 4.0 by integrating machine workload data into a Prognostics and Health Management (PHM) algorithm (Converso, 2023). This systematic literature review examined predictive maintenance (PdM) in military contexts, highlighting challenges, principles, application scenarios, and technical methodologies (Jovani, 2023). This paper introduced the adaptive Gaussian mixture scheme refined probability distributions (Zhang, 2022), achieving Quantitative and qualitative analyses highlighted the potential and challenges, advocating for improved data schemas and interoperability to advance PdM in infrastructure facilities effectively (Seyed, 2022). This study investigated the use of probabilistic neural networks (PNNs) (Nashed, 2022). Results from case studies on cover-plated beams and process pipework demonstrated that these models effectively captured variability in data distribution parameters, offering more accurate fatigue predictions compared to deterministic approaches. This paper surveyed ML and DL methods for fault detection and diagnosis (FD/D) in induction motors (IMs) within Industry 4.0, highlighting DL's dominance since 2015 (Drakaki, 2022). This study developed a predictive maintenance system for the manufacturing industry, utilizing historical sensor data to forecast equipment failures and optimize maintenance schedules (Kane, 2022). The study proposed a high-level architecture for AI-enabled EIS, highlighting challenges like cost optimization and data interoperability, while underscoring AI's potential to enhance system efficiency and innovation (Zdravkovic, 2021).

This paper proposed an efficient fault detection and diagnosis model for PV systems, achieving 98.5% accuracy using three sequential PNN models (H. Zu, 2020). This survey paper reviewed predictive maintenance methodologies, highlighting the benefits over traditional methods like cost savings and preventing failures (Tyagi, 2020). This study conducted a systematic review of literature on predictive maintenance (PdM) within Industry 4.0, focusing on machine learning and reasoning applications (Dalzochio, 2020). This paper developed machine learning- based Prognostic and Health Management (PHM) models using sensor data to diagnose faults in transformer systems within smart grids (Li, 2018). HD Pass employed Apache Spark for real-time predictive maintenance of HDDs in data centres, aiming to pre-empt failures and optimize reliability, resulted in reduced downtime, extended equipment life, and enhanced operational efficiency in cloud computing environments (Chuan_Jun Su, 2018). The researcher developed a method for rapid fault detection and localization in power transmission lines using three-phase voltage data to derive the Concordia pattern and classify faults with a Probabilistic Neural Network (PNN) (S. Mishra, 2016). The researcher introduced Self-Adaptive Probabilistic Neural Net- works (SaPNN), which autonomously adjusted the Spread parameter for enhanced predictive accuracy in transformer fault diagnosis (Yi-JH, 2016). The researcher developed a fault diagnosis method for gears using vibration analysis and wavelet transform for predictive maintenance (Devendiran, 2015). The researcher developed a MATLAB-based approach using Independent Component Analysis (ICA) and supervised learning classifiers, notably PNN, to improve condition monitoring in power plants by effectively detecting and categorizing bearing malfunctions in noisy environments (Hameed, 2013). The researcher developed two innovative approaches for predicting meteorological time series data: an Evolving Polynomial Neural Network (EPNN) and a hybrid polynomial neural network with genetic algorithm (PNN-GA), both achieving high accuracy and outperforming traditional models (Mellit, 2010). The researcher developed a neural network-based method for monitoring machine health at the Refinery of 'Milazzo' in Italy, successfully identifying faults not covered in the training data (Crupi, 2004). The researcher identified that traditional maintenance scheduling was inadequate for high- reliability industries, which required predictive maintenance using advanced monitoring to predict failures and prioritize maintenance (Mohammad Azam, 2002).

3 DATASET

Previously we worked on sample data set but this time target was to work with real time data. For that purpose, I have to finalize one equipment for further research work. And positively we got the opportunity to monitor the ma- chine health. The dataset used in this study is sourced from 'Radhan Plastics', a company established in 2008 as a Partnership Firm. 'Radhan Plastics' specializes in manufacturing films, tubing, rolls, bags, and covers from materials such as EVA (Ethyl Vinyl Acetate), VCI (Vapour Corrosion Inhibitor), Bubble, LDPE. Their products are available in various designs, colours, sizes, and shapes to meet di- verse customer needs. These products find extensive application in : Rubber compounding, Pharmaceuticals, Food industry, Agriculture, Industrial packaging, Auto component/spares packing, Other industrial packaging applications The company's manufacturing facility is located in the picturesque area of 'Pirangut', near Pune, India. Their clientele spans across India, including cities such as Roorkee, Mumbai, Jammu, Bangalore, and Hyderabad. Hence work to present in this seminar was to test the algorithms with real time data. This sample data file contains 3 main groups of data as:

1. Total Number of Sensors: 04
2. Data Recorded: 3 Months per minute [Dec.2022–Feb.2023]
3. Total count: 50302

Sr. No.	December	January	February
1	7279	24395	18628
		43023	
Label	Test Data set	Train Data Set	

Figure 1: Category as per Machine Status

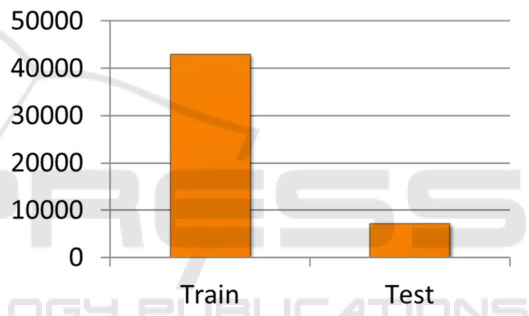

Figure 2: Distribution of Data Set

Here, three months of data utilised. With the help of time-based splitting, the data divided into train and test, where 2 months of data used as train dataset and rest used as test dataset.

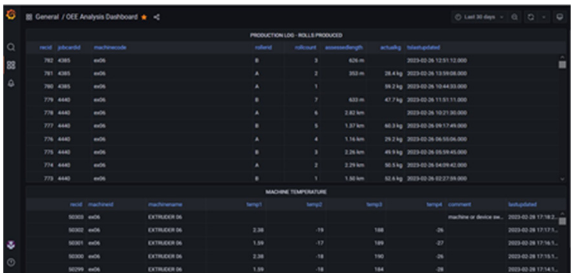

Figure 3: Dashboard of Data set

The above figure shows the dashboard. Dataset is categorized as Production Log and Machine Temperature. The upper part "Production Log" used for OEE calculation. Bottom part, Machine Temperature, with tracking these 4 sensors predicts the failures.

Bottom side machine temperature dashboard with recid, machine id, machine name, with 4 temperature sensors. They named as temp1, temp2, temp3, temp4.

Automatic comment gets generated whenever machine gets switched off [Reasons are unknown], to identify these reasons PdM is needed.

Table I: Machine Tags With Description

Sr. No.	Tags	Description
01	ex06	Extruder Machine Name
02	recid	The serial number, updated at new entry
03	Roller id	It can be either A or B, each has different features
04	Roller count	Number of rolls produced for the job card during the shift
05	Assessed length	Roll length [ranges from 10 m to 9.53 km]
06	Actual kg	Weight of the roll [range is 10 kg to 92.1 kg]

Here, the dataset is shown for complete 1 year for OEE as well as PdM Calculations. The figure is showing data recorded for 18th April. Last entry of 18th April is at 11 PM of 35.8 kg at that time message popped up as machine is switched off.

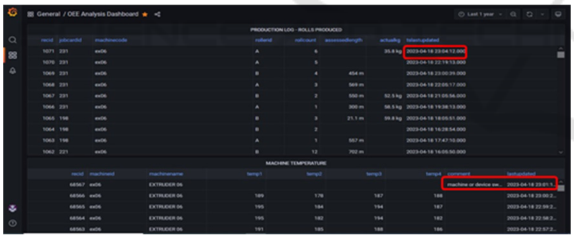

Figure 4: Dashboard of Data set of 1 Year

The data for this study considered from 'Radhan Plastics' online platform known as the "OEE Analysis Dashboard". This dashboard provided real-time data in .csv format, which can be downloaded for further analysis. The dataset includes information from four temperature sensors used to monitor the temperature of a plastic extruder machine. Plastic Extruder Machine: It is used in manufacturing to melt and shape plastic materials into continuous profiles or shapes by forcing them through a die. It plays a crucial role in industries such as packaging, construction, and automotive, producing items like pipes, sheets, and filaments.

Next figure shows csv file data recorded for 28th February. Range of temperature sensor is [-1 to 240 degree Celsius]. Maximum limit is 240 degree Celsius, for this particular reading machine should provide an alert before any failure occurs. Through the timestamp data, information extracted as start of shift and of shift and unplanned downtime during the shift. This helps in calculating various loses at field.

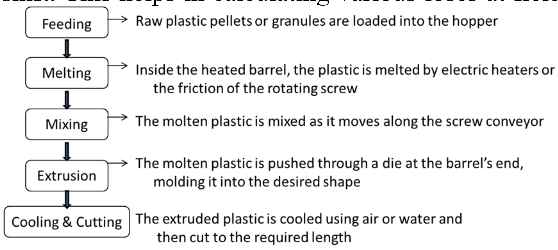

Figure 5: Working Principle of Plastic Extruder Machine

Deep learning, a subset of machine learning derived from artificial neural networks, is characterized by multiple non- linear processing layers. Its goal is to learn hierarchical representations of data. The field is rapidly evolving, with new models being developed frequently. The deep learning community is highly collaborative, offering numerous high- quality tutorials and books. Thus, this text provides only a brief overview of key deep learning techniques used in machine health monitoring. The review covers four major deep architectures—Auto-encoders, CNNs, RNNs, and their variants. Researchers have developed predictive maintenance algorithms using both machine learning and deep learning. Initially, two machine learning algorithms were created for testing purposes to compare their results with those of deep learning algorithms. These algorithms are now being tested with real-time data. The selected machine learning and deep learning algorithms include BPNN, CNN, SVM, Bi-LSTM, LSTM, and PNN.

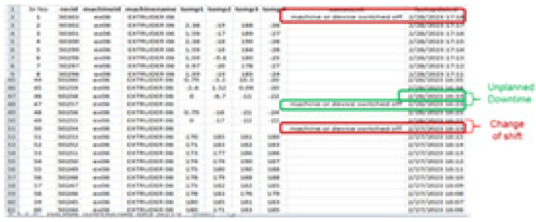

Figure 6: Dataset CSV File

4 METHODOLOGY

In this research, MATLAB R2023b software will be utilized to test all the selected algorithms. The dataset comprises 19,679 rows, each containing data from four temperature sensors. Initial testing indicates that the Probabilistic Neural Network (PNN) performs better for this specific dataset. The research will involve the following steps:

4.1 Data Pre-Processing

Data pre-processing involved cleaning and normalizing the dataset to ensure consistency and accuracy. This step included handling any missing or anomalous values, which could have otherwise skewed the results. The dataset was then split into training and testing subsets to allow for model validation and performance assessment.

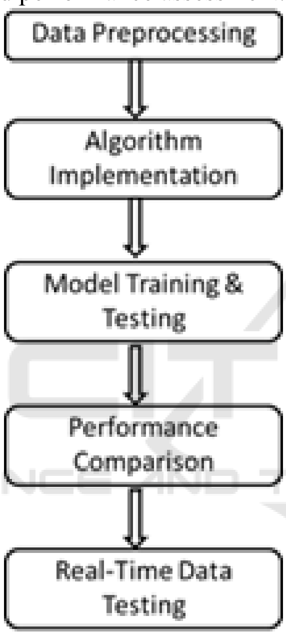

Figure 7: Methodology

4.2 Algorithm Implementation

The implementation phase involved setting up the chosen machine learning and deep learning algorithms: BPNN, CNN, SVM, Bi-LSTM, LSTM, and PNN. Each algorithm was configured with appropriate parameters and hyper-parameters tailored to the specific characteristics of the dataset. MATLAB 2023b was used to code and run these algorithms.

4.3 Model Training & Testing

During model training, each algorithm was trained on the training subset of the data to learn the underlying patterns. After the training, the models were sending for testing subset to estimate their predictive accuracy. We do have various performance matrices to test the model accuracy. Performance metrics like accuracy, precision, recall, and F1-score were used to assess the models.

4.4 Performance Comparison

The performance of each and every algorithm got compared with each other. The comparison is performed to determine which model is best. This comparison involved analysing various performance metrics and identifying strengths and weaknesses of each algorithm. The goal was to find the most effective model for predictive maintenance.

4.5 Real-Time Data Testing

In the final phase, the best-performing algorithms were applied to real-time data to validate their effectiveness in a live environment. This testing helped ensure that the models could handle real-world conditions and provide reliable predictions for machine health monitoring. The performance in this phase confirmed the practical applicability of the models.

5 RESULTS & DISCUSSION

The following table shows the results of various algorithms, where each was run five times with a learning rate of 0.001 and a maximum epoch size of 1000. The table highlights that the Probabilistic Neural Network (PNN) achieved the highest accuracy at 99.70%. Thus, for the applied real-time dataset consisting of 19,679 rows of 4 temperature sensors from a plastic extruder machine, PNN was observed to be the best- performing model.

Table 2:: Model Performance Comparison

(Learning Rate: 0.001, Epoch: 1000)

Models / Max Epochs	1	2	3	4	5
BILSTM	58.20	49.26	58.20	58.20	58.20
BPNN	58.20				
LSTM	71.29	77.18	73.32	79.91	65.39
CNN	91.30	92.13	91.19	91.74	91.30
PNN	99.70				

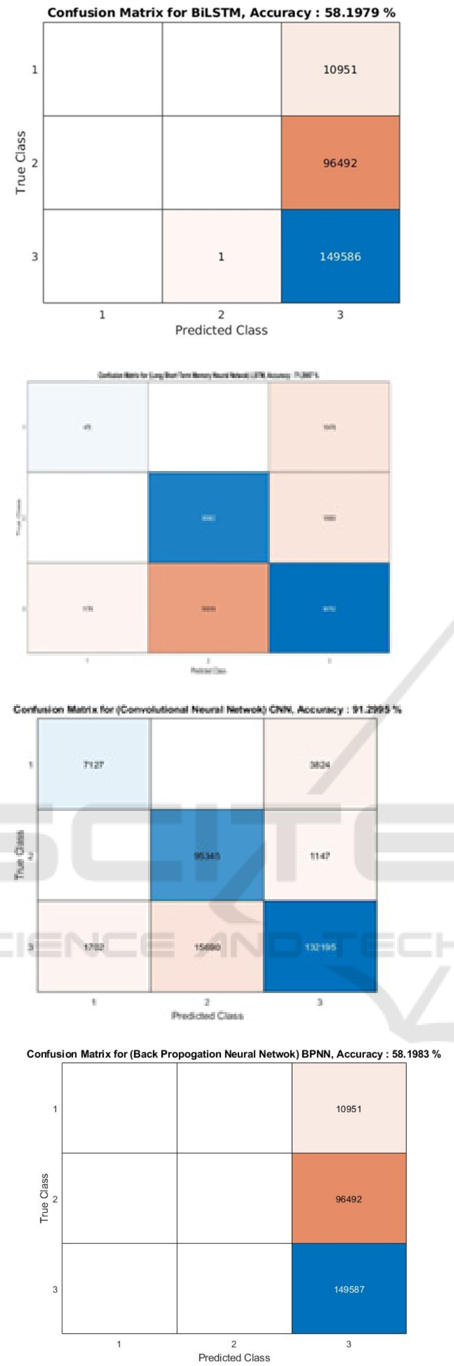

Figure 8: Confusion Matrix of BILSTM, LSTM, CNN, BPNN.

6 CONCLUSIONS

The Predictive maintenance is very much essential. It ensures optimal performance as well as prevents costly down-times. The costly downtimes considering machines like extruder machines are very crucial as it requires a consistent product quality. This study is purposely focused on use of real-time data. The data is from four temperature sensors fitted in a plastic extruder machine. The temperature sensor ensures precise temperature control and high-quality output. The dataset analysed comprised 19,679 rows of data. A range of machine learning (ML) and deep learning (DL) algorithms were tested. Tested algorithms are as follows:

Probabilistic Neural Network (PNN), Backpropagation Neural Network (BPNN), Convolutional Neural Network (CNN), Support Vector Machine (SVM), Long Short Term Memory (LSTM), and Bidirectional LSTM (BiLSTM). Each algorithm tested for the five consecutive times with a learning rate of 0.001 and a maximum epoch size of 1000.

The results proved that PNN, ML algorithm achieved the remarkable accuracy of 99.70%. This makes it the best- performing model for the applied real-time dataset. PNN's ability to handle noisy data and its robustness against outliers contributed to its superior performance. Additionally, PNN's architecture allowed for efficient processing of large datasets and required minimal parameter tuning compared to more complex algorithms like LSTM and BiLSTM.

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