Enhancing Predictive Maintenance: Integrating XGBoost and LSTM Models with Autoencoder for Improved Machine Health

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Abstract— **: The future of the automobile industry revolves around three basic factors: increased reliability, lower costs, and more effective operation as well as upkeep. Many manufacturers have recently placed a strong emphasis on predictive maintenance since it enables the early detection of equipment problems before they become serious. This implies increased difficulties in the car manufacturing process and, consequently, increased maintenance requirements. Artificial intelligence and machine learning applications enable the advancement and updating of existing maintenance methods in the manufacturing of battery-powered car engines with condition surveillance, troubleshooting, and anticipatory maintenance; timely identification may prevent a great deal of time and money. These advances in technology and their impact in the manufacturing sector by way of the Revolution of 4.0, or Industry 4.0, for short, are interesting. This study proposes two methods that use two deep learning models for anomaly detection to enable predictive maintenance. In the first, different failure kinds are classified using an XGBOOST; in the second, different defects are classified using a Recurrent Long Short-Term Memory neural network (LSTM) with Autoencoder. While the LSTM model adjusted better at identifying high temperatures on generator bearings—a failure that occurred frequently throughout the study—it was discovered that the original model could generalize various types of failures. Look away**

Keywords:- Machine learning, Artificial neural network , Criminal Identification, CNN , neural network , deep learning,

**Introduction**

Industrial equipment and machinery breakdowns are especially difficult to deal with since they generate functional degradation and other adverse impacts which includes higher expenses for manufacturing, more lengthy delivery delays, and lower profits for the industry. Even with tight maintenance routines in place, no disruption is still attainable when essential collapse parameters are not correctly monitored, which makes control measures worthless. Industries have implemented metrics for success to tackle these issues, with Key performance indicators, or KPIs being a key component. Within the setting of Total Productive Maintenance, vital metrics like Mean Time without Failures (MTBF), Mean Time to Repair (MTTR), and Overall Equipment Effectiveness (OEE) are essential. However, going above and beyond conventional techniques is necessary to provide the best possible service and save downtime. Various machine learning algorithms have come to light as efficient tools for maintenance planning in new studies. As stated by Traini et al. (2019), time-based predictive maintenance has shown better precision by leveraging sensors and machine learning models, thus lowering the consequences of unexpected breakdowns in maintenance operations. Notably, scholars such as Bohdan (2019) highlight the accuracy of ARIMA prediction models, which closely resemble neural network outcomes and provide benefits like lower processing and storage costs. In addition, Liu et al. (2019) suggest using Support Vector Machines (SVM) for condition-based monitoring, which makes use of historical data to forecast the machinery's remaining useful life. In building predictive models, this study expands on the idea of taking into account historical information from the past and the machine's current state. Furthermore, Zhou et al. (2019) discussed how long-short-term memory, or LSTM, has been used to anticipate errors based on non-linear time series datasets. Regression techniques based on Extreme Learning Machines (ELMs) may be more predictive than others, although issues with memory consumption and computational constraints have been brought up (Da Silva et al., 2020). Imbalances datasets present difficulties for Support Vector Machines (SVM) (Zhao et al., 2019), highlighting the approach of choosing the right approaches for particular data situations.

**Literature review**

The vital role that industrial pumps play in effective production highlights the increasing importance of predictive maintenance. A case study focuses on the use of Radio Frequency (RF) technology and vibration data to forecast pump failures and provide early detection with a seven-day heads-up. Reliability is increased by the study's extended testing period and practical problem-focused approach; nevertheless, challenges with data preparation and sensor integration underscore the need for more research in the use of intuitive maintenance planning.

Predictive maintenance with intricate decision rules is made possible by the combination of Cutting Machine IIOT, PLC, and sensor data. The Random Forest (RF) algorithm is successful in predicting several machine stages, with a precision rate of 95%. Despite greater algorithmic complexity, accuracy is improved by using a variety of classifiers.

Current and voltage waveform data are used as an alternative in the analysis of a 2.2 kW induction motor, applying both single and double classifiers. These methods are efficient in discovering inter-turn short circuits; however, the multiple classification approach produces better results, despite using two training models is more costly as well. However, the algorithm, which makes use of Random Forest (RF), does not take certain voltage conditions into account.

This study uses SVM, RF, and GBM models for predictive maintenance using real vending machine data. Two models are developed: one for two-stage prediction and the other for diagnostics. While the model for forecasts at a certain level exceeds standard prediction models, its average precision and accuracy are only 80 percent for the diagnostics model and 80 percent for the forecasting model.

Several machine learning algorithms, such as k-mean, PCA, HC, and fuzzy C-Means clustering, are used in the exhaust fan fault identification. While empirical techniques are reliable for detecting faults, algorithms that cluster are more effective in identifying different stages of faults. Comparing Principal Component Analysis (PCA) to model-based techniques yields better results. However, the study is conducted on a small

dataset, and T2 statistics complexity increases after a specific point in time..

This work examines a packaging robot and uses Artificial Neural Network (ANN) with the MLP strategy to analyze vibration, temperature, and humidity data in order to handle unexpected downtime events. The method lowers the cost of unscheduled downtime considerably. The study relies on manually gathered offline data and blends theoretical and empirical observations of defects; it does not use IoT technology.

An Artificial Neural Network (ANN) model analyzes time-domain vibration signatures for critical materials in a study of a 1200 rpm wind turbine using vibration data. The model completes the task of classifying safe and dysfunctional states with 92.6 percent rating performance. But more complex computation is needed due to the required feature complexity.

When analyzing operation information from a printing machine, the Linear Regression (LR), XGBoost, and Random Forest (RF) models work well with various measurement systems. The models outperform LR's judgment thresholds, specifically RF and XGBoost. When comparing the algorithms' Receiver Operating Characteristic (ROC) performance, they are equal. Nonetheless, the intricacy of data processing and missing data resulting from errors in the data collection procedure drive up expenses.

This study uses GBM, RF, XGBoost, and NN classification algorithms to examine woodworking industrial machines using vibration, current, and temperature data. It achieves 98.9 percent precision and accuracy. An extensive data the flow processing unit is subjected to predictive maintenance (PdM), which uses recorded files to assess the machine's condition every 24 hours. The study gathers inaccurate data from a woodworking machine and applies statistical methods to address the propagation of uncertainty.

The C-MAPSS tool, which integrates data from multiple sensors sourced from the NASA Ames Prognostics Data Repository, to investigate the use of an LSTM classifier in the context of turbofan engines. The dataset consists of 4 subsets totaling 708 trajectories, with 21 columns representing 21 sensors and synthetic data in each subset. For pro-prognostics choices and projections, the study uses a DPM system; however, no degradation model or particular Remaining Useful Life (RUL) function is specified. Rather, it concentrates on giving probabilities of system failure over various time frames, while providing a model for assessing inventory and maintenance

The C-MAPSS NASA simulation dataset is used in this study to apply an LSTM model to analyze sensor and engine operational data, with 14 inputs and 4 outputs. The model predicts the current life condition of engine components by implementing LSTM on Apache Spark for large-scale datasets, which helps with early break down the identification in manufacturing facilities.

This literature reviews SVM Regression with a R kernel applied to time series sensor data from the C-MAPSS dataset, with an emphasis on the aircraft's gas turbine engine. When tested with simplified data simulations, the model operates better than standard SVM outcomes for forecasts estimation in various time-series tasks.