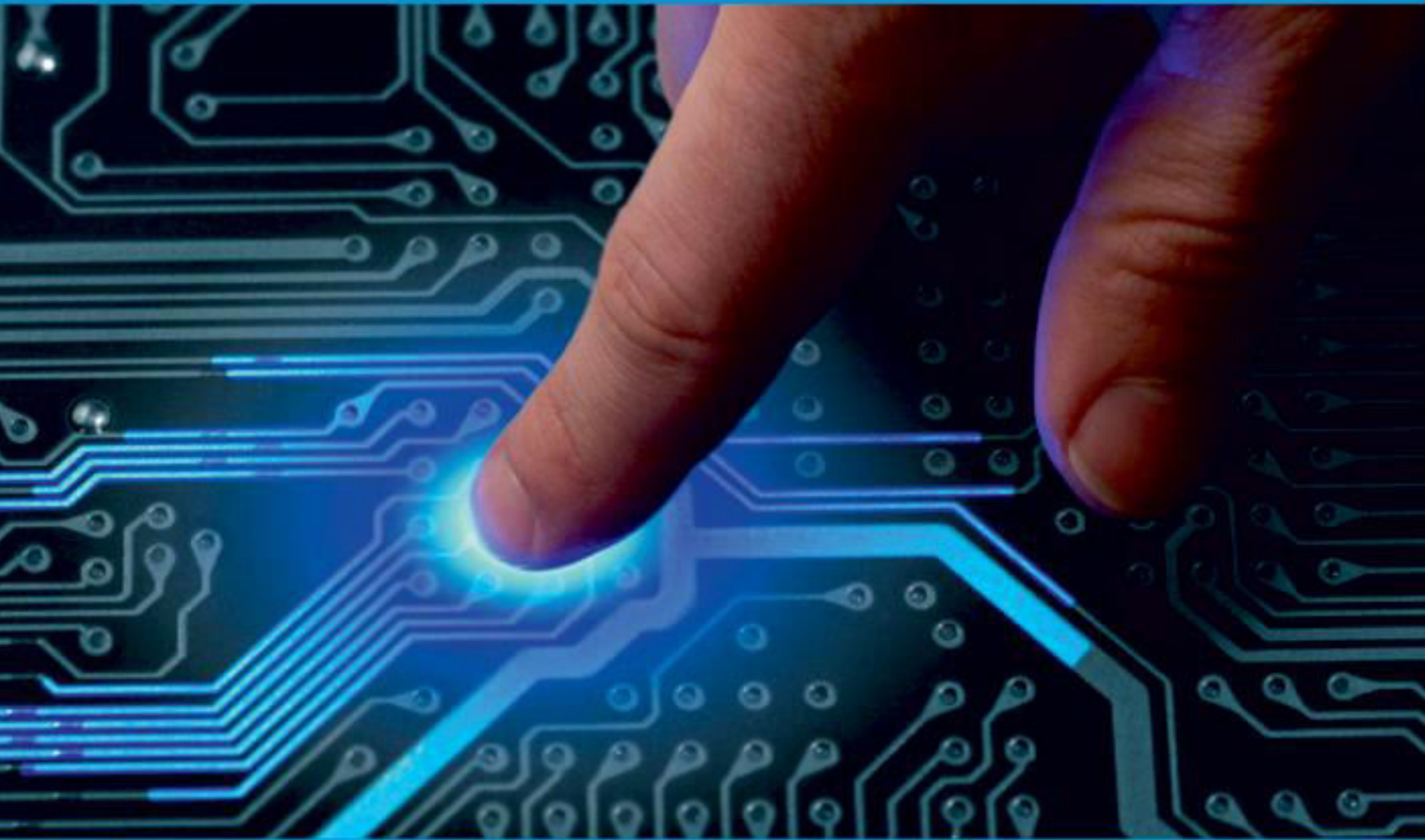
IJIRCCE

e-ISSN: 2320-9801 | p-ISSN: 2320-9798



INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH

IN COMPUTER & COMMUNICATION ENGINEERING

Volume 11, Issue 7, July 2023

Impact Factor: 8.379

International Journal of Innovative Research in Computer and Communication Engineering

| e-ISSN: 2320-9801, p-ISSN: 2320-9798| www.ijircce.com | |Impact Factor: 8.379 |

|| Volume 11, Issue 7, July 2023 ||

| DOI: 10.15680/IJIRCCE.2023.1107011 |

A Novel AI Framework for Anomaly Detection and Predictive Maintenance in Heterogenous Networks

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ABSTRACT: Two key methods in the fields of data analysis and deep learning are anomaly detection and predictive maintenance. While predictive maintenance uses data to predict when equipment or machinery is likely to fail so that maintenance can be planned pre-emptively, anomaly detection involves spotting patterns or events that deviate from the norm. Both methods are frequently employed in many different sectors, such as manufacturing, healthcare, and finance, to increase productivity, cut costs, and improve safety. An overview of these two methods, their uses, and the difficulties in successfully putting them into practice are given in this research article.

KEYWORDS: Data analysis, deep learning, spotting patterns

I. INTRODUCTION

The fields of anomaly detection and proactive network maintenance have seen substantial progress thanks to deep learning techniques. Convolutional neural networks (CNNs), recurrent neural networks (RNNs), and long short-term memory (LSTM) are examples of deep learning algorithms that have been used to identify anomalies and forecast maintenance needs in a variety of applications.

Deep learning algorithms can extract complex features from raw data, such as network traffic, sensor data, or log files, for anomaly identification. Then, these characteristics can be used to spot anomalies that might be challenging to find using conventional statistical techniques. Deep learning models can also adjust to changes in the distribution of the data and increase the precision of their identification over time.

Deep learning models can recognise patterns in sensor data to anticipate equipment breakdowns in predictive maintenance. These models can recognise early indications of failure and offer suggestions for upkeep procedures to reduce apparatus downtime. By estimating the equipment's remaining usable life and choosing the ideal time for maintenance, deep learning models can also be used to optimise maintenance schedules. However, the requirement for substantial quantities of labelled data to train the models makes using deep learning for anomaly detection and predictive maintenance difficult. Deep learning models can also be computationally costly and demand a lot of computing power.

However, new developments in deep learning hardware and algorithms have made it simpler to create and implement deep learning models for anomaly detection and proactive network maintenance.

II. TYPES OF DEEP LEARNING ALGORITHM FOR ANOMALY DETECTION

The use of deep learning algorithms for anomaly spotting and proactive maintenance is widespread. Here are a few instances.

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Convolutional Neural Networks (CNNs): CNNs are frequently used for image processing jobs, but they can also be used for anomaly detection and preventive maintenance on time-series data from sensors. CNNs are able to autonomously extract key characteristics from the data and recognise patterns that might point to unusual behavior or equipment failure.

Recurrent Neural Networks (RNNs): RNNs are frequently used for speech and natural language processing because they are built for sequential input. Through the capture of dependencies between time steps and the prediction of future values, RNNs can be used to analyse time-series data for predictive maintenance and anomaly detection.

Networks with long short-term memory (LSTM): A class of RNN called LSTMs is capable of handling long-term relationships and excels at handling time-series data with intricate temporal dynamics. For preventive maintenance, LSTMs have been applied to industrial equipment and wind turbines.

Autoencoders: Unsupervised deep learning models that are capable of learning low-dimensional approximations of high-dimensional data are known as autoencoders. By reconstructing typical data and highlighting data points that substantially differ from the reconstructed data, they can be used for anomaly detection.

Deep learning models called "generative adversarial networks" (GANs) can produce new data that is comparable to training data. By creating new data and comparing it to the real data to find differences, GANs can be used for anomaly detection.

III. PROBLEM STATEMENT

Develop and implement efficient deep learning models that can precisely detect anomalies and anticipate maintenance needs in complex systems such as networks, machinery, and industrial equipment. This is the problem statement for anomaly detection and predictive maintenance using deep learning. Designing deep learning models that can manage highly dimensional and complex data, adjust to changing data distributions, and offer accurate predictions with high reliability is the primary challenge. A major issue that needs to be solved is the requirement for large amounts of labelled data for training these models. The objective is to use deep learning to increase the speed and accuracy of anomaly detection and preventative maintenance in a variety of industrial uses.

IV. PROPOSED FRAMEWORK

Anomaly detection and predictive maintenance are predicted using deep learning techniques. NeuralProphet is used here. Built on top of PyTorch, NeuralProphet is a Python module for time-series forecasting. For the purpose of creating and refining deep learning models particularly for time-series data, it offers a high-level API. The library supports a variety of models, including neural networks (NNs), autoregressive (AR) models, and NNs and NNs combined. Moreover, it supports other kinds of seasonality, such as yearly, weekly, and daily seasonality, as well as exogenous factors, which can assist the model absorb more data.

Anomaly detection: By forecasting the predicted values and contrasting them with the actual values, NeuralProphet may be used to identify abnormalities in time-series data. An anomaly is identified if the discrepancy between the predicted and actual numbers is greater than a certain threshold. This can aid in seeing odd trends in sensor data, picking up on device malfunctions, and forecasting downtime.

NeuralProphet may also be used for predictive maintenance by estimating the equipment's remaining usable life. NeuralProphet can forecast when a machine is likely to fail and suggest maintenance steps before the failure takes place by evaluating sensor data from machines. As a result, unexpected downtime may be decreased, equipment dependability can be improved, and maintenance plans can be optimised.

V. CALCULATION OF ANOMALIES

The performance of the model is displayed above with the value of Root Mean Square Error (RMSE) and Mean Absolute Error (MAE).

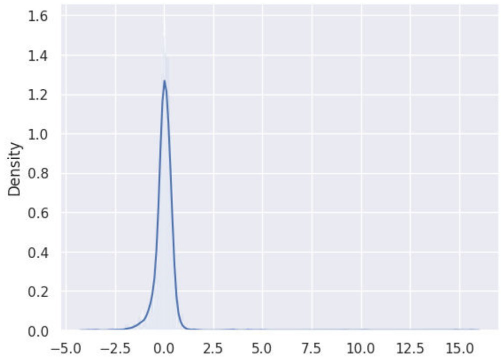

Fig1: The above predictive maintenance graph depicts the number of anomalies in the dataset.

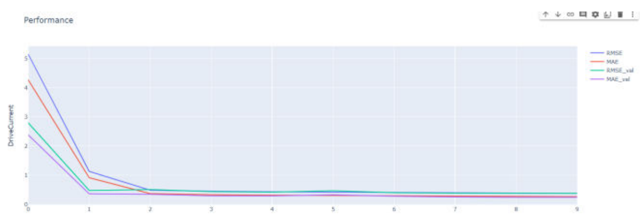

Fig.2. The performance of the model

	ds	y	yhat1	ar1	trend	season_yearly	season_weekly
0	2007-12-10	9.5908	NaN	NaN	NaN	NaN	NaN
1	2007-12-11	8.5196	NaN	NaN	NaN	NaN	NaN
2	2007-12-12	8.1837	NaN	NaN	NaN	NaN	NaN
3	2007-12-13	8.0725	NaN	NaN	NaN	NaN	NaN
4	2007-12-14	7.8936	NaN	NaN	NaN	NaN	NaN
...	...	...	...	...	...	...	...
2368	2014-06-04	7.4759	7.657046	1.790667	6.136144	-0.227578	-0.042187
2369	2014-06-05	7.5883	7.383906	1.538758	6.135555	-0.231076	-0.059331
2370	2014-06-06	7.2464	7.432385	1.626407	6.134966	-0.234352	-0.094636
2371	2014-06-07	7.1033	7.159762	1.503775	6.134378	-0.237373	-0.241018

Fig.3. The performance of the model

VI. CONCLUSION

Generally, NeuralProphet is a strong and adaptable library for time-series forecasting, with several features and capabilities that make it suited for a variety of applications, including anomaly detection and predictive maintenance. For data scientists and analysts working with time-series data, its adaptability, automated feature selection, quick training, interpretable output, imputation of missing values, and simplicity of usage make it a desirable option.

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