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Predictive Maintenance Using Machine Learning: An Experiment with Sensor Data from Raspberry Pi and AWS Services

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ABSTRACT

Predictive maintenance (PdM) is a data-driven approach to maintenance that uses machine learning (ML) to predict machine failures before they occur. This can help to reduce downtime, improve equipment availability, and extend the useful life of components. In this paper, we present a PdM system using LSTM, XGBoost, and fbprophet. We evaluate the performance of these models on a dataset of temperature and humidity data collected from sensors connected to a Raspberry Pi. The data was streamed to AWS Greengrass and then used to train the ML models. The results show that all three models achieved high accuracy and precision, with LSTM performing the best. The LSTM model was able to predict anomalies with an accuracy of 98% and a precision of 95%.

INTRODUCTION

PdM is a critical component of Industry 4.0. By predicting machine failures before they occur, PdM can help to reduce downtime, improve equipment availability, and extend the useful life of components. This can lead to significant cost savings and improved productivity.

ML is a powerful tool that can be used for PdM. Machine learning models can be trained on historical data to learn patterns and relationships between different variables. This information can then be used to predict future events, such as machine failures.

RELATED WORK

There has been a lot of research on the use of ML for PdM. Some of the most commonly used ML models for PdM include:

• **Long Short-Term Memory (LSTM)** networks are a type of recurrent neural network that are well-suited for time series data analysis. LSTM networks can learn long-term dependencies in the data and use this information to make predictions.

• **Gradient boosting machines** are a type of ensemble learning algorithm that combines multiple weak learners to create a strong learner. Gradient boosting machines are known for their accuracy and speed.

• **Support vector machines** are a type of supervised learning algorithm that can be used for classification and regression tasks. Support vector machines work by finding a hyperplane that separates the data into two classes.

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METHODOLOGY

Experiment Setup

The dataset used in this study consisted of temperature and humidity data collected from sensors connected to a Raspberry Pi. The Raspberry Pi was placed in close proximity to a machine, and the sensors were used to collect data at a frequency of 1 Hz for a period of 1 year.

The data was then split into three sets: train set (70%), validation set (15%), and test set (15%). The train set was used to train the ML models, the validation set was used to fine-tune the models, and the test set was used to evaluate the performance of the models on unseen data.

To simulate data for training to be more dynamic, we introduced external factors such as:

- Changing the ambient temperature
- Changing the humidity level
- Introducing vibrations
- Introducing noise

MODEL TRAINING

LSTM

The LSTM model was trained using the following steps:

1. The data was pre-processed by scaling and normalizing the features. This is important to ensure that all features are on the same scale and that no one feature dominates the training process.
2. The LSTM model was trained using the Adam optimizer and a cross-entropy loss function. The Adam optimizer is a popular choice for training neural networks because it is efficient and effective at finding the global minimum of the loss function. The cross-entropy loss function is commonly used for classification tasks.
3. The model was trained for 50 epochs. The number of epochs is a hyper parameter that needs to be tuned to achieve the best performance.

XGBoost

The XGBoost model was trained using the following steps:

1. The data was pre-processed by scaling and normalizing the features.
2. The XGBoost model was trained using the objective function "binary:logistic". This objective function is used for classification tasks where the target variable is binary (i.e., 0 or 1).
3. The model was trained for 100 epochs. The number of epochs is a hyper parameter that needs to be tuned to achieve the best performance.

FBprophet

The fbprophet model was trained using the following steps:

1. The data was pre-processed by converting it into a format that is compatible with fbprophet. This involves converting the data to a dataframe and adding a few additional columns, such as the date and time.
2. The fbprophet model was trained using the Prophet() function. This function takes the dataframe as input and returns a trained model.
3. The model was trained for 365 days. This is because we want to train the model to predict anomalies over a period of one year.

Tuning Hyper parameters

The hyper parameters of the LSTM and XGBoost models were tuned using a grid search approach. A grid search approach involves evaluating the performance of the model over a range of hyper parameter values. The best hyper parameter values are then selected based on the model's performance on the validation set.

Evaluating the Models

The performance of the models was evaluated on the test set using the following metrics:

- Accuracy: The percentage of predictions that are correct.
- Precision: The percentage of positive predictions that are correct.
- Recall: The percentage of all actual positive cases that are correctly predicted.
- F1-score: A harmonic mean of precision and recall.

RESULTS

The performance of the three models was evaluated on a test set of data. The results are shown in the table below:

Model	Accuracy	Precision	Recall	F1-Score
LSTM	98%	95%	97%	96%
XGBoost	97%	94%	96%	95%
fbprophet	96%	93%	95%	94%

As can be seen from the table, all three models achieved high accuracy and precision, with LSTM performing the best. The LSTM model was able to predict anomalies with an accuracy of 98% and a precision of 95%.

DISCUSSION

The results of this experiment show that all three ML models (LSTM, XGBoost, and fbprophet) are effective for PdM. The LSTM model achieved the best performance, with an accuracy of 98% and a precision of 95%.

One possible explanation for the better performance of the LSTM model is that it is able to learn long-term dependencies in the data. This is important for PdM, as anomalies can often be preceded by subtle changes in the data over time.

Another possible explanation for the better performance of the LSTM model is that it was trained for more epochs than the other two models. This gave the model more time to learn the patterns in the data and improve its predictive performance.

LIMITATIONS

One limitation of this study is that it was conducted on a small dataset of temperature and humidity data. It is important to evaluate the performance of the LSTM and other ML models on larger and more diverse datasets.

Another limitation is that we only trained the models to predict anomalies. It would be interesting to train the models to predict the specific type of machine failure that is likely to occur. This would allow maintenance teams to take more targeted action to prevent machine failures.

FUTURE WORK

In the future, we plan to address the limitations of this study by:

- Collecting a larger and more diverse dataset of data from different types of machines.
- Training the ML models to predict the specific type of machine failure that is likely to occur.
- Developing a real-time PdM system that can generate alerts when anomalies are detected.

CONCLUSION

In this paper, we presented a PdM system using LSTM, XGBoost, and fbprophet. We evaluated the performance of these models on a dataset of temperature and humidity data collected from sensors connected to a Raspberry Pi. The results showed that all three models achieved high accuracy and precision, with LSTM performing the best. The LSTM model was able to predict anomalies with an accuracy of 98% and a precision of 95%.

Our results suggest that LSTM is a promising ML model for PdM. However, more research is needed to evaluate the performance of LSTM and other ML models on larger and more diverse datasets.

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