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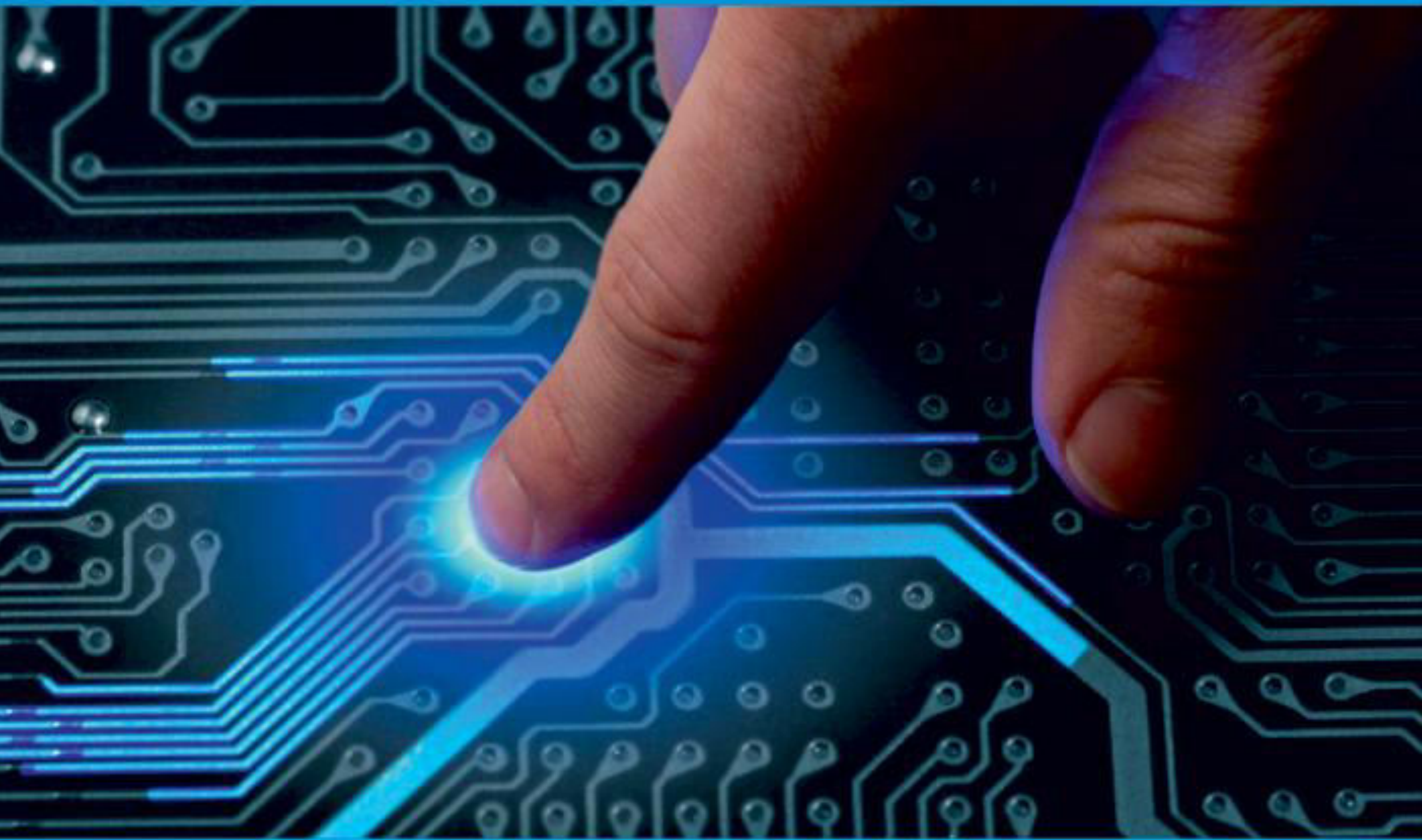

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Condition Monitoring using IIOT for Predictive Maintenance of Machine

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ABSTRACT: Conditional Monitoring of machines is very important to reduce the money invested in replacing the whole mechanical component which can be instead achieved by continuous upgrades on the current machines which reduces the drastic breakdown of the machines and improves the machine life, Although these methods are implemented in many MNC machinery companies, It's not being used in the conventional machinery factories due to which they are forced to pay on machine maintenance very regularly, This proposed system which can take the sensor data from the machine (Vibration, thermal, Acoustic) and is used to predict the life of the machine, predict the breakage of the machine and letting the user know the changes to be made to improve the efficiency of the machine by replacing the faulty component to reduce the inefficiency. The paper mainly focuses on Machine Learning part of the system which is used for prediction and detection of faults in the machine while machine is performing its activities, The main contribution of this work to solve the issues was the use of KNN algorithm or K-Neighbours Algorithm and is specifically used to predict the date and time at which the machine could break down and give real time data on what the components are experiencing and predict the utmost time after which it has to be repaired or replaced, and due to improve messaging and data sharing techniques the report is share with the user using E-mail services and text messaging format which will increase the user interaction and speedy recovery of the machine components.

KEYWORDS: Machine Condition Monitoring, Machine Leaning, K-Neighbour's Algorithm (KNN), Internet of things (IoT)

I. INTRODUCTION

Condition monitoring is a Leading requirement in the Heavy duty manufacturing industry that has very bulky and costly machineries that require absolute maintenance and replacement of important instruments in order to keep up the efficiency and quality of the product being manufactured every single minute, however monitoring manually is very tedious and demands a skilled human power which will be a more tolling asset and less accurate output, which can be overcome by the implementation of Conditional monitoring of machines that will predict and gives accurate data by collecting the real-time data from the machines which can be further used to predict the date and time at which the machine components needs to be refurbished of changed completely, which will reduce the time loss due to machine maintenance, which could be used for production if not lost, so this will be a efficient method to get a accurate prediction of the condition of the machine, which could be difficult for human resource to manage and interpret the conclusions

II. RELATED WORK

A predictive Maintenance system will allow the user to analyze the machine health by analyzing the data and the prediction by the machine could be used to date down the time at which the machine could break down and needs to be changed or repaired, There is automation everywhere which reduce the human errors which can be reduced by accurate prediction of the machine model, this can be implemented that can make work easier by understanding the prediction of the machine. [1]. The speed of detection and accuracy is important for the Condition monitoring of machines and implementing in real-time scenarios. In real-time scenario, the temperature, Vibration variation and anomaly detected is a major concern. Hence this methodof classification is confirmed as this is been proved to be simple and powerful [2]. By making using of the Industrial sensors Temperature and Vibration is measured which is later fed to a Programmable logic controller (PLC). Thus, PLC act as a Gateway to feed the information to PC/Computer. [3]. Data in the form of machine sensor measurements are recorded in real-time during the manufacturing process and a graph is then plotted with predetermined threshold limits that reflect the capability of the process. [4]. By using Anomaly Detection Algorithm, the data points that falls within the thresholds indicates that everything is normal and working operating as

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expected with some natural variation that is expected as part of the process. [5]. Data pre-processing is very important in this module because without proper data pre-processing, we would have so much noise in our data that will prevent us from having the accurate prediction. We use anomaly detection algorithm to remove the possible data points that are not required for the data analysis stage, this will remove the noise from the dataset and will be ready to be trained and analysed. [6]. Feature Extraction stage is necessary because certain features have to be extracted so that they are unique for each machine. After the decision is made that a problem in the machine is present, then the last frame is taken into consideration and features. [7]. Classification of the attributes are done for proper training of the machine learning algorithm, the classification is done using few classifying algorithms, which will be better for getting the accuracy on prediction of machine components [8]. After classification for prediction we use LSTM model to do future forecasting and use the data to find out if the machine condition is normal or not.

III. PROPOSED ALGORITHM

A. *Design Considerations:*

- AC Motor
- Sensors to Receive the data from the motor in real time
- Storing the values in a CSV file as data collection
- Considered all possible paths at beginning.
- Temperature data is used to find out the future prediction using LSTM model

B. *Description of the Proposed Algorithm:*

Aim of the proposed algorithm is to do Future Forecasting on the motor data to know if the motor is normal or abnormal. The proposed algorithm is consists of three main steps.

Step 1: Gathering the motor Data, from the sensors.

- Get in data on the running machine (e.g. changes in temperatures, vibrations)
- By making use LM393 (Vibration sensors), LM35IC (Temperature sensors), ZMPT101B (AC Voltage sensor) the required vibration, temperature and voltage fluctuation values are noted.

Step 2: Selection Criteria:

Suppose there are two categories, i.e., Category A and Category B, and we have a new data point x1, so this data point will lie in which of these categories. To solve this type of problem, we need a K-NN algorithm. With the help of K-NN, we can easily identify the category or class of a particular dataset.

- **Step-1:** Select the number K of the neighbors
- **Step-2:** Calculate the Euclidean distance of **K number of neighbours**
- **Step-3:** Take the K nearest neighbors as per the calculated Euclidean distance.
- **Step-4:** Among these k neighbors, count the number of the data points in each category.
- **Step-5:** Assign the new data points to that category for which the number of the neighbor is maximum.
- **Step-6:** Now classify normal vaues and abnormal values as 0 and 1 respectively
- **Step-**7: Our model is ready.

Step 3: Predicting the Future Condition using LSTM model:

RNNs can keep track of arbitrary long-term dependencies in the input sequences. The problem with vanilla RNNs is computational (or practical) in nature: when training a vanilla RNN using back-propagation, the long-term gradients which are back-propagated can "vanish" (that is, they can tend to zero) or "explode" (that is, they can tend to infinity), because of the computations involved in the process, which use finite-precision numbers. RNNs using LSTM units partially solve the vanishing gradient problem, because LSTM units allow gradients to also flow *unchanged*. However, LSTM networks can still suffer from the exploding gradient problem

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IV. PSEUDO CODE

Pseudo-code for the DE algorithm with LSTM classifier
Define the size of the population NP, D dimension of problem,
crossover rate Cr, scale factor F.

Initialization:

Initialize the population St=0 = {sts, Sb$_1$}, I = 1,..., Np which each individual uniformly distributed in the range [s ^{low}, s ^{high}]

While the termination criteria is not met

For each individual, target vector, in the population NP

Mutation: Select three individual from the population randomly and generate a donor vector v using the following mutation equation: v_1 = sip + F_1 (Sir + siq)

Crossover: Compute the trial vector for the ith target vector of u $_{j,i}^{t+1}$

$$u_{j,i}^{t} = \begin{cases} v_{i,j}^{t} & if \;\; r_i \leq c_r \; or \; j = J_{rand} \\ s_{i,j}^{t} & otherwise \end{cases}$$

Selection: Apply LSTM classifier as fitness function fand evaluate sand u:

If f(s $_i^t$) < f(u $_i^t$) then s $_i$ $^{t+1}$= u $_i^t$

Else s $^{t+1}$ = st

End For

End While

V. SIMULATION RESULTS

After the machine complete training on the data set that have been cleaned and revised the machine learning model will use its trained memory to analyze each and every data point that it has trained on already and predicts the anomaly or normal condition and then using LSTM model it predicts the date and time at which the machine could breakdown or should have a repair or refurbishment, this can be monitored by using dashboards that display the results accordingly.

The (Fig1) shows the motor assembly which has a motor fixed with different sensors on to, namely vibration and thermal sensors, and other components, (Fig2) and (Fig3) shows the collected data and the prediction of the condition of the motor by getting the data in real time, (Fig3) shows the confusion matrix of the False true and other components and the accuracy of the prediction and the different averages (Fig4) shows how we train the LSTM model with the collected dataset (Fig6) shows the graph after applying the test data for the trained LSTM model.

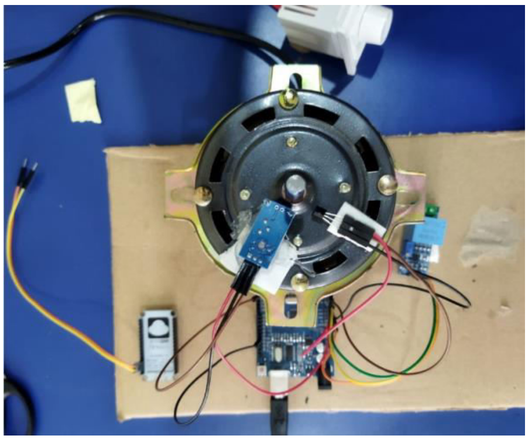

Fig.1. Motor Assembly

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 100000 entries, 0 to 99999
Data columns (total 3 columns):
 #   Column       Non-Null Count   Dtype
---  ------       --------------   -----
 0   Temperature  100000 non-null  int64
 1   Vibration    100000 non-null  int64
 2   Result       100000 non-null  int64
dtypes: int64(3)
memory usage: 2.3 MB

Filename: Motor_Test/input.txt
['41', '90']
['41', '90']
Motor condition is abnormal

Filename: Motor_Test/input.txt
['37', '63']
['37', '63']
Motor condition is Normal
```

Fig. 2. Data Condition analysis

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```
Confusion Matrix :
[[50000     0]
 [    0 50000]]
Accuracy Score : 1.0
Report :
              precision    recall  f1-score   support

           0       1.00      1.00      1.00     50000
           1       1.00      1.00      1.00     50000

    accuracy                           1.00    100000
   macro avg       1.00      1.00      1.00    100000
weighted avg       1.00      1.00      1.00    100000
```

	Temperature	Vibration	Result
0	38	75	0
1	41	101	1
2	38	63	0
3	40	116	1
4	38	66	0
...	...	...	...
99995	39	100	1
99996	37	77	0
99997	43	113	1
99998	36	60	0
99999	43	102	1

100000 rows × 3 columns

Fig. 3. Data set and Confusion Matrix

```
Model: "sequential_1"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
lstm_1 (LSTM)                (None, 60, 50)            10400
_________________________________________________________________
lstm_2 (LSTM)                (None, 50)                20200
_________________________________________________________________
dense_1 (Dense)              (None, 25)                1275
_________________________________________________________________
dense_2 (Dense)              (None, 1)                 26
=================================================================
Total params: 31,901
Trainable params: 31,901
Non-trainable params: 0
_________________________________________________________________
None
```

```
In [20]:
1  #Train the model
2  model.fit(x_train, y_train, batch_size=1, epochs=5)

Epoch 1/5
420/420 [==============================] - 24s 58ms/step - loss: 0.0609 0s - loss:
Epoch 2/5
420/420 [==============================] - 24s 58ms/step - loss: 0.0303
Epoch 3/5
420/420 [==============================] - 25s 59ms/step - loss: 0.0271
Epoch 4/5
420/420 [==============================] - 25s 59ms/step - loss: 0.0260 0s - loss:
Epoch 5/5
420/420 [==============================] - 26s 62ms/step - loss: 0.0245
Out[20]: <keras.callbacks.callbacks.History at 0x1a275075dc8>
```

Fig. 4. Training Data Set with LSTM model

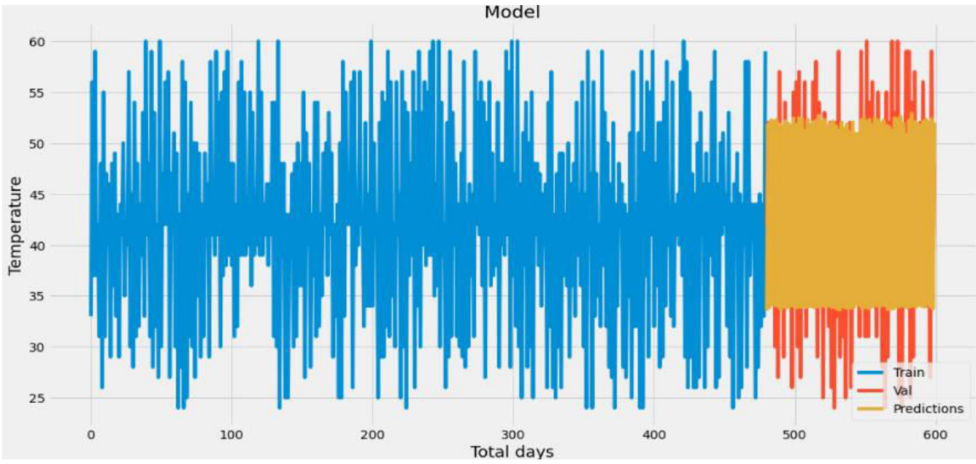

Fig. 5. Data analysis and prediction of a graph

VI. CONCLUSION AND FUTURE WORK

The end result what we could draw from this project is that early prediction helps in reducing the manufacturing cost and this prediction can be drawn using various parameters such as vibration, temperature, where various data from different parameters are collected together and analyzed according to a standard threshold value for the respective parameters once the values cross the threshold value along with combination of other parameters go wrong then we can conclude that the machine is towards the destruction and it alerts the users about the same. Hence predictive maintenance of machines can be formed using latest IIOT technology. For future enhancement the accuracy and the precise timing of the machines breakdown can be implemented without a glitch in data interpretation and visualization, having better visualization effects improves the understanding of the problem even better, we can also improve the motor condition by monitoring individual components..

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