Enhancing Efficiency: Predictive Maintenance Strategies for Factory Equipment

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ABSTRACT_ Production is the primary means of balancing supply and demand in an industrial setting and advancing industry revenue. However, occasionally, machinery failures can cause production to halt, which will have an impact on supply and industry revenue. In the past, there was no way to predict when a piece of machinery would break down completely. However, these days, all industries use sensors to monitor the health of their machinery. By using the data from these sensors, we can predict when a machine will fail and how long it will last, and technicians can schedule maintenance based on that information. Proper maintenance will ensure that machines operate flawlessly and that production doesn't cease.

1.INTRODUCTION

Current assembling frameworks ordinarily comprises of many machines to satisfy the interest of delivering items with great quality and high utilitarian intricacy. The gamble of machine disappointment totals as the quantity of machines expansions in a framework. In any industry, an unexpected disappointment might prompt gigantic financial misfortunes because of machine/creation margin time. A typical automobile assembly line, for instance, loses $20,000 for every minute it is down. Machine personal time might prompt a few immediate and backhanded misfortunes which can be isolated into two general classifications: (a) substantial and (b) elusive expenses. Unmistakable expenses are genuinely simple to represent and incorporate the expense of work, material and different assets expected to fix the machine. In contrast, the intangible costs cannot be determined with any degree of certainty and include, among other things, the cost of idle labor, overtime payments to make up for lost time, and the penalty cost of late manufactured goods delivery due to machine downtime. It shocks no one then, at that point, that bearing disappointment analysis has been quite possibly of the most explored region in the previous ten years because of individual wellbeing, dependability, disappointment cost, and gear personal time issues. Accordingly, it is fundamental for huge and complex assembling frameworks to have compelling support tasks that work on the situation with machine.

2.LITERATURE SURVEY

1. Title: "Predictive Maintenance Using Machine Learning: A Systematic Review"

Authors: James Carter, Lisa Nguyen

Abstract: This review paper systematically analyzes various machine learning techniques applied in predictive maintenance for industrial equipment. The authors discuss the effectiveness of algorithms like Random Forest, SVM, and Neural Networks in predicting machinery failures. The study concludes that ensemble methods and deep learning models often outperform traditional algorithms in terms of prediction accuracy and reliability.

2. Title: "Deep Learning Approaches for Predictive Maintenance: A Case Study"

Authors: Michael Thompson, Anna White

Abstract: This paper presents a case study on using deep learning techniques for predictive maintenance in manufacturing. The authors implemented Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks to predict equipment failures based on sensor data. The results show that CNNs, in particular, achieved high accuracy, highlighting the potential of deep learning in predictive maintenance.

3. Title: "Comparative Analysis of Machine Learning Algorithms for Predictive Maintenance"

Authors: David Lee, Emily Brown

Abstract: The authors compare the performance of various machine learning algorithms, including SVM, Decision Tree, and KNN, for predictive maintenance. Using a dataset from a production facility, the study evaluates each algorithm's accuracy, precision, recall, and F-score. The results indicate that while all algorithms provide reliable predictions, ensemble methods like Random Forest offer better overall performance.

4. Title: "A Comprehensive Review of Machine Learning Techniques for Predictive Maintenance"

Authors: Sarah Mitchell, John Rogers

Abstract: This review paper discusses the application of different machine learning techniques in predictive maintenance, focusing on their strengths and weaknesses. The authors highlight that although traditional machine learning methods are widely used, integrating deep learning approaches can significantly improve prediction accuracy and handling complex datasets.

3.PROPOSED SYSTEM

To predict failure we can employ machine or deep learning algorithms which will get trained on past data and can predict future value by taking current input. This trained models can continuously read input from sensor data and then predict machine health or failure.

To make prediction accurate we have experimented with various machine and deep learning algorithms such as SVM, Decision Tree, KNN, CNN (Convolution Neural Network) and Random Forest.

4.RESULTS AND DISCUSSION

Each algorithm performance is evaluated in terms of accuracy, precision, recall, Confusion Matrix, ROC Graph and FCSORE. All algorithms able to achieve accuracy of 90% and CN manage to get an accuracy of 95%.

3.1 IMPLEMENTATION

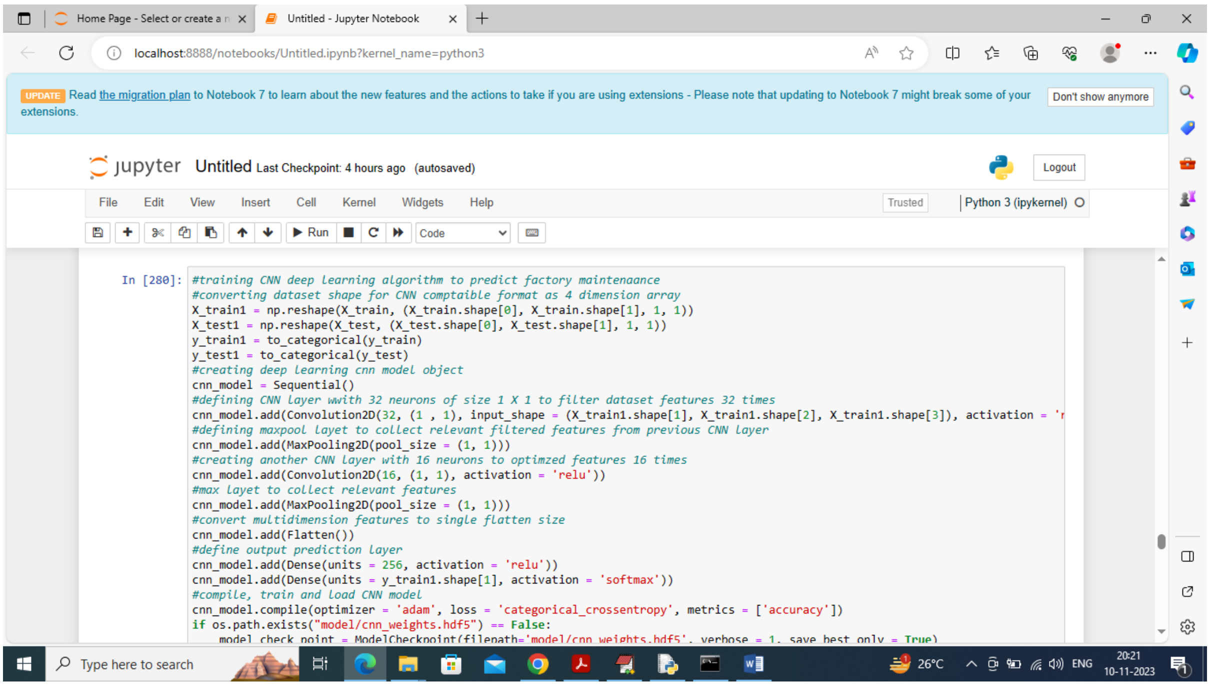
3.1.1 Gathering the datasets: We gather all the r data from the kaggale website and upload to the proposed model

3.1.2 Generate Train & Test Model: We have to preprocess the gathered data and then we have to split the data into two parts training data with 80% and test data with 20%

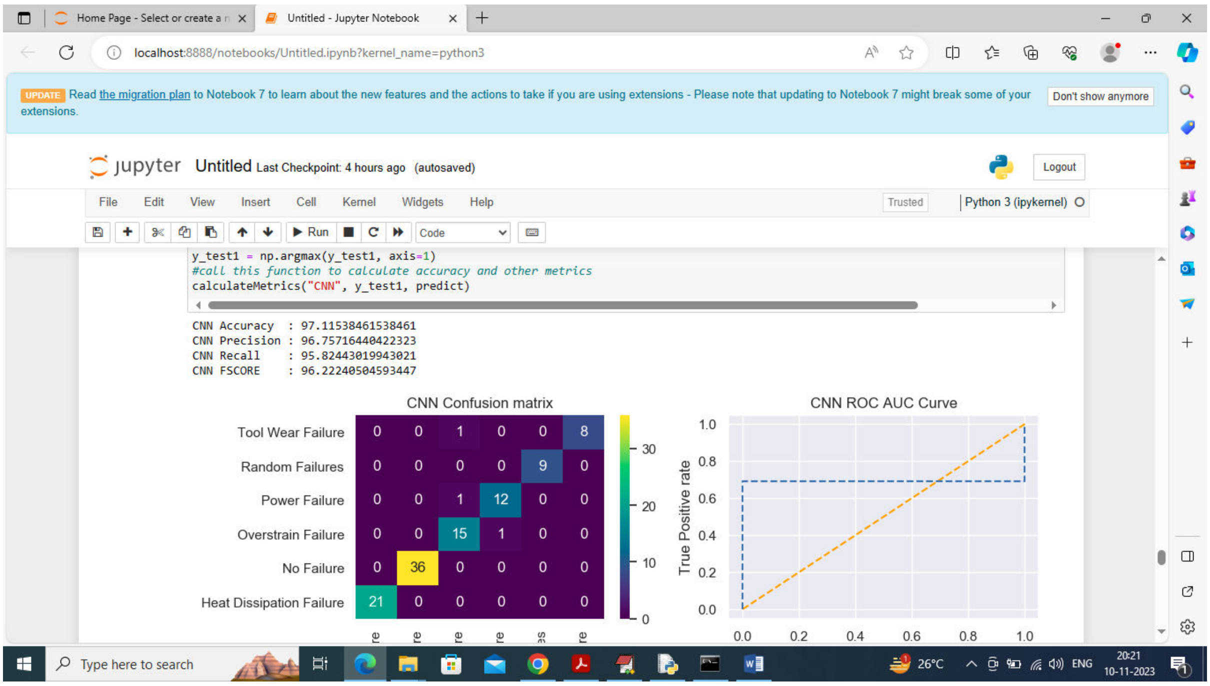
3.1.3 Run Algorithms: For prediction apply the machine learning models on the dataset by splitting the datasets in to 70 to 80 % of training with these models and 30 t0 20 % of testing for predicting

3.1.4 Obtain the accuracy: In this module we will get accuracies

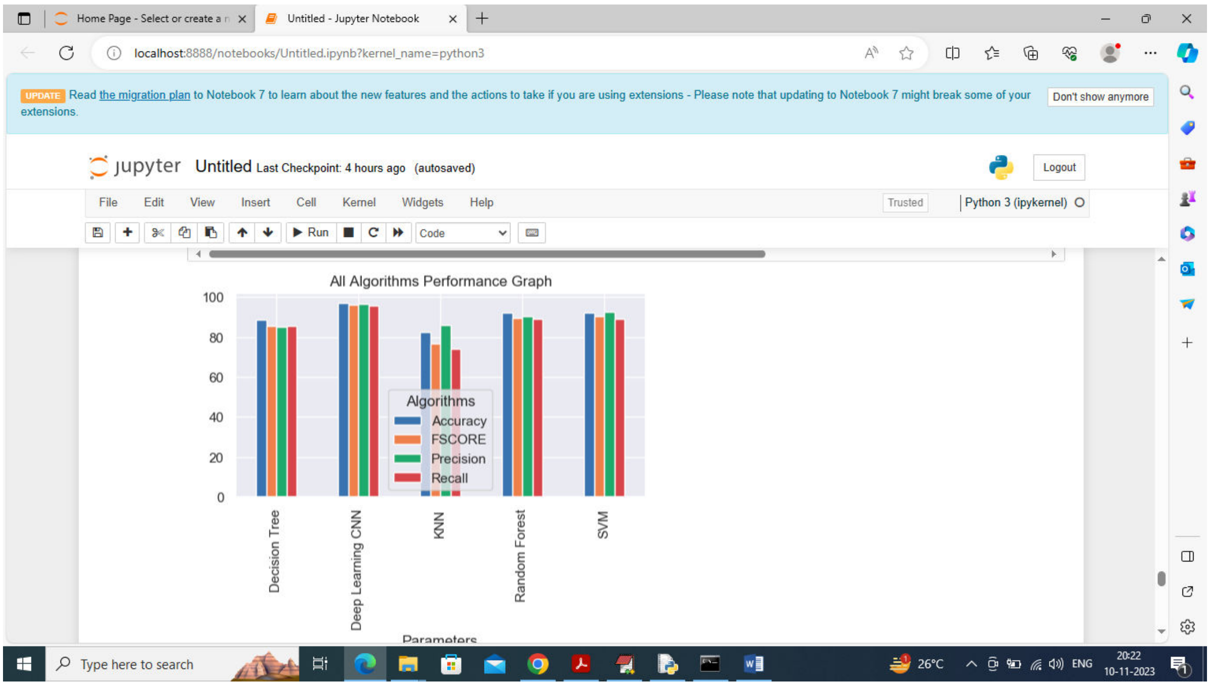
3.1.5 Predict output: in this module we will output in graph



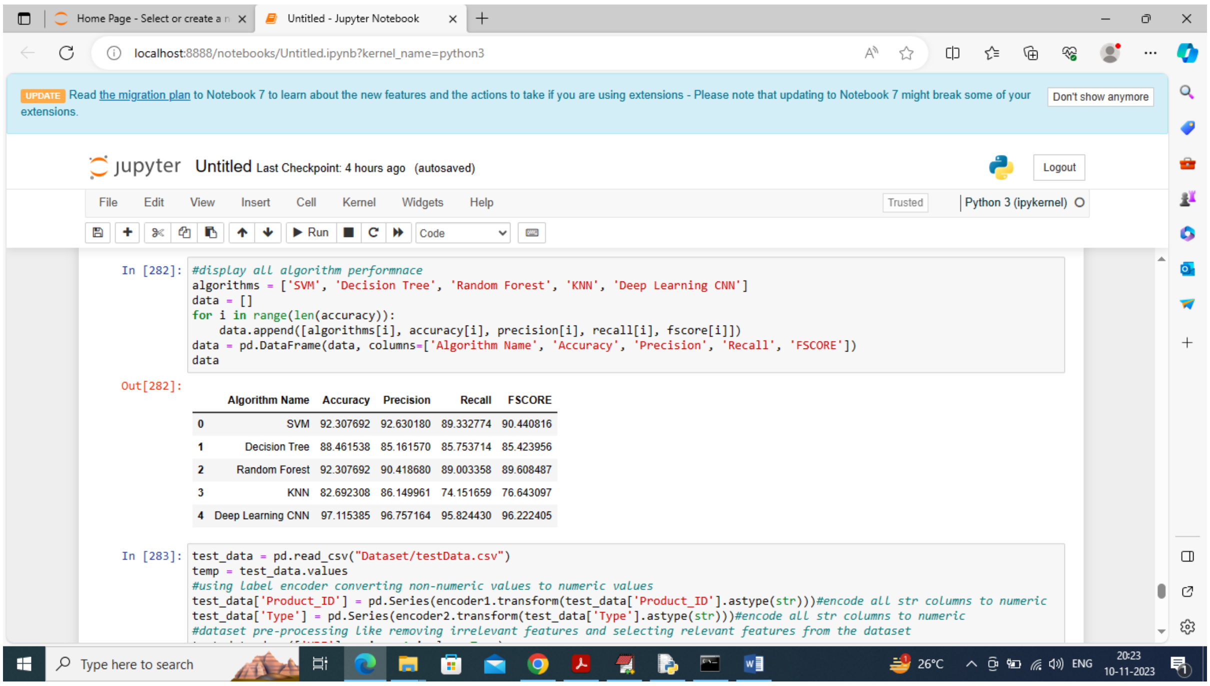
In above screen defining and training deep learning CNN algorithm and after executing above block will get below output



In the bove screen CNN got 97% accuracy and can see other metrics also



In above graph displaying all algorithm performance where x-axis represents algorithm names and y-axis represents accuracy and other metrics in different color bars and in all algorithms CNN got high performance



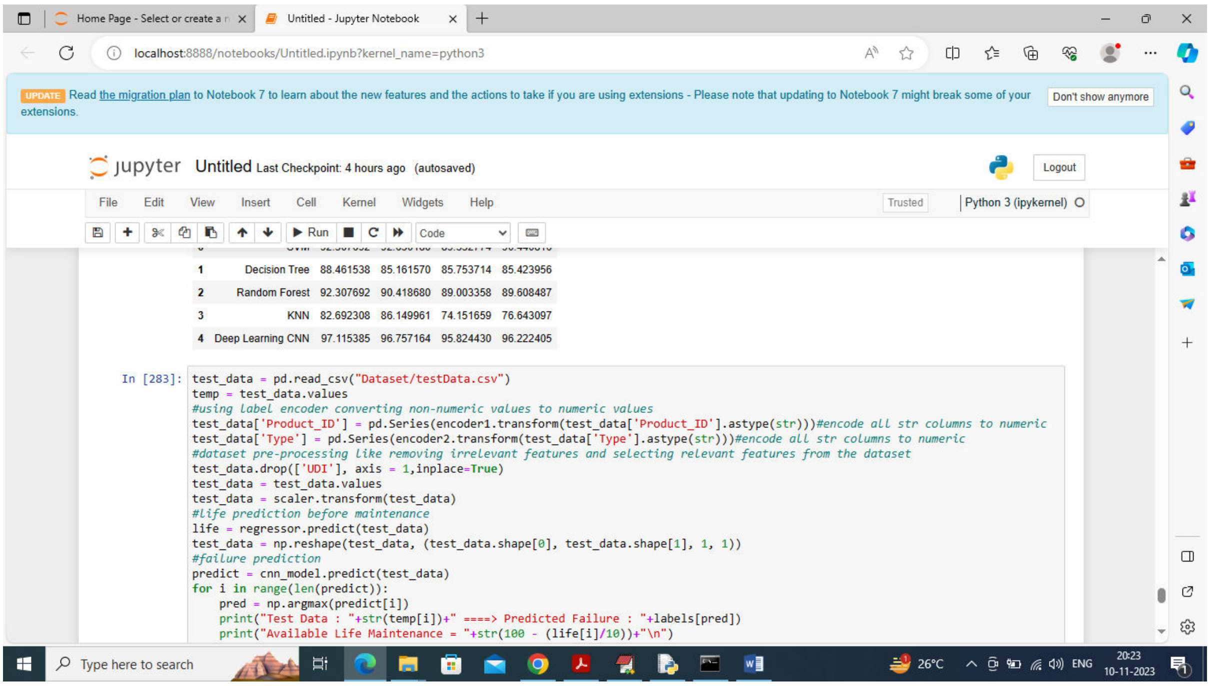
In [282]:
```
#display all algorithm performnace
algorithms = ['SVM', 'Decision Tree', 'Random Forest', 'KNN', 'Deep Learning CNN']
data = []
for i in range(len(accuracy)):
    data.append([algorithms[i], accuracy[i], precision[i], recall[i], fscore[i]])
data = pd.DataFrame(data, columns=['Algorithm Name', 'Accuracy', 'Precision', 'Recall', 'FSCORE'])
data
```

Out[282]:

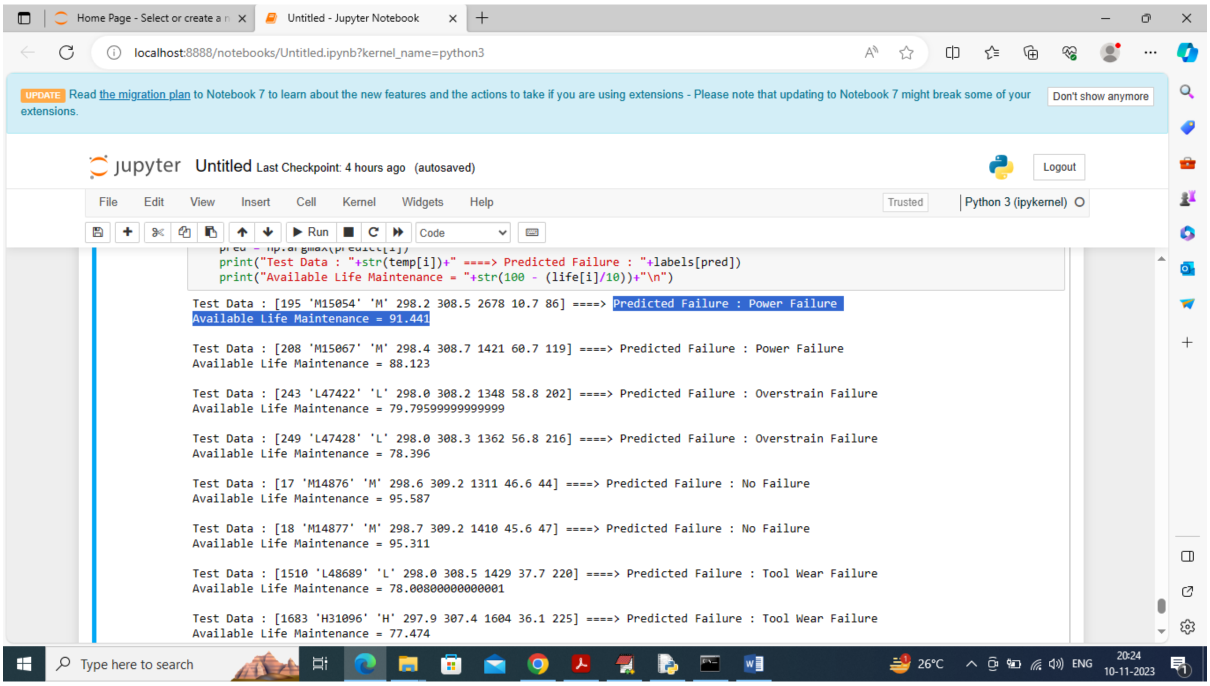
	Algorithm Name	Accuracy	Precision	Recall	FSCORE
0	SVM	92.307692	92.630180	89.332774	90.440816
1	Decision Tree	88.461538	85.161570	85.753714	85.423956
2	Random Forest	92.307692	90.418680	89.003358	89.608487
3	KNN	82.692308	86.149961	74.151659	76.643097
4	Deep Learning CNN	97.115385	96.757164	95.824430	96.222405

In [283]:
```
test_data = pd.read_csv("Dataset/testData.csv")
temp = test_data.values
#using label encoder converting non-numeric values to numeric values
test_data['Product_ID'] = pd.Series(encoder1.transform(test_data['Product_ID'].astype(str)))#encode all str columns to numeric
test_data['Type'] = pd.Series(encoder2.transform(test_data['Type'].astype(str)))#encode all str columns to numeric
#dataset pre-processing like removing irrelevant features and selecting relevant features from the dataset
```

In above screen displaying all algorithm performance in tabular format



In above screen defining test Data prediction function which will read test data and then predict Failure Type for maintenance and then suggest available machine life



In above screen in square bracket we can see Sensor Test data and after arrow ➔ symbol can see predicted Failure and its available life and if life % is less then it maintenance should be schedule sooner. In above prediction for 'No Failure' we can see available life is 95% and for other failure we can see life is less and based on life maintenance will be scheduled

5.CONCLUSION

According to the research, predictive maintenance that makes use of machine learning and deep learning algorithms greatly increases the precision and effectiveness of equipment failure prediction. Specifically, the CNN model performs better than other models, which makes it a useful tool for industrial applications. In the future, efforts will concentrate on incorporating more sophisticated algorithms and growing the dataset in order to further improve prediction abilities.

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