INTRODUCTION:

A convolution neural network is a part deep neural network. Usually a convolution neural networks consist of many neurons which is similar to human brain neural network . It collects the input and converts it into a series of hidden layers. Hidden layer is made up of neurons A convolution neural network different kinds of activation function, which is used for passing the output to the next set of layer. A recurrent neural network (rnn) is a class of artificial neural network where connections between nodes from a directed graph along a sequence . This allows it to exhibit temporal dynamic behavior for a time sequence . The term recurrent neural network is used indiscriminately to refer to two broad class of neural networks with a similar general structure, where one is a finite impulse and other is infinite impulse .

Long Short Term Memory (LSTM) in this we don't have memory cell value equivalent to activation value. We also introduce an additional gate called forget Gate. It gives us the optional to keep the previous values and also to add update this gate with additional value from update gate. LSTM is most popular now for dealing with long term dependencies. We also have a output gate. LSTM is more robust than GRU, but people use both of them based on applications .The functioning of LSTM can be visualized by understanding a LSTM network is comprised of different memory blocks called cells. There are two states that are being transferred to the next cells ; the cell sate and the hidden state .the memory blocks are responsible for remembering things and manipulations to this memory is done through three major mechanisms, called gates.

A time series is a series of data indexed in time order . Mostly a time series is a sequence of data taken at successive equally spaced points in the time. Thus it is a sequence of discrete time data . example of time series are heights of ocean tides , counts of sunspots and the daily closing value of the Dow Jones industrial average. Time series analysis comprises methods for analyzing time series data in order to extract meaningful statistics and other characteristics of the data . Time series forecasting is the use of the model to predict future values based on previously observed values. Time series data have a natural temporal ordering. This makes time series analysis distinct from cross sectional studies. Time series analysis is classified into two classes of analysis frequency domain methods and time domain methods. One description of statistics is that it provides a means of transferring knowledge about a sample of a population to the whole population and other related populations which is not necessarily, which is not necessarily the same as prediction over time. When information is transferred across the time often to specific points in time the process is knows as forecasting .Simple or fully formed statistical models to describe the likely outcome of the time series in the immediate future, given knowledge of the most recent outcomes(forecasting) . A common goal of the time series is extrapolating past behavior into the future.

PROBLEM STATEMENT:

In this project work we are taken "HOUSEHOLD POWER CONSUMPTION FORECASTING" as our problem .This project work is based on time series prediction From the given problem statement we are going to predict the next values with the help "Recurrent neural network" In this problem statement there are totally seven parameters are as follows ;Date, Global active power, Global reactive power, Voltage, Global intensity, Sub merting1, Sub merting2, Sub merting3and Time.

- Global active power : The total active power consumed by the household in a period of time (KW).
- Global reactive power : The total reactive power consumed by the household in a period of time(KW).
- Voltage : Average voltage consumed in the house hold expressed in volts.
- Global intensity : Average current intensity of the household (amps).
- Sub metering 1: Active energy for a kitchen and other appliances present in that room . (watt hours of active energy)
- Sub metering 2: Active energy for a laundry which mainly consist of a washing machines and drier (watt hours of active energy).
- Sub metering 3 : Active energy for climate control devices such as air conditioner , fans, room heaters (watt hours of active energy.
- Sub metering 4 :Active energy by small electricity consumption..

REASON FOR DOING THIS PROJECT:

We take this project to understand the wastage power in day to day usage. Household energy conservation is a very practical and realistic approach to conserve the energy in day to day usage . Electricity is a secondary source of energy . It basically derived from sources like coal , natural gas, nuclear reactions , sunlight ,wind , hydropower. In this most of the sources are renewable and other are non renewable .For example energy we are getting from nuclear fission and nuclear fusion are very difficult process. While comparing to the past and present the usage electricity is predominate increase over the year .

The fact for increase in power consumption in every household is due to inventions of more kind of electrical home appliances and improper usage of electricity. Energy conservation refers to energy which was used in different kinds of purposes. The energy conservation reduces the consumption of energy per capita on a demand .Which reduces the rise in energy cost . The reduction emission , energy conservation is one of the important method to prevent the climatic changes . More than 8% of the electricity we consuming is wasted with and without our knowledge . The government of India passed act for conservation of energy in the year 2001 . It shows the series trouble in power consumption . Most of the electricity is used for domestic purpose . Most of the villages in India are not getting proper electricity . A survey say that about 31 million Indian homes are not getting electricity properly , mostly in villages .

In this project work our aim is to determine electricity consumption in household and predict the future values . By using our project work we easily predict the value of the for the future power consumption and also we also develop the new appliances which are consuming very less amount of power consumption . For a problem there are various kinds of solution like that we are giving the one of the solution for power consumption . we are using previous years data for our forecasting . This project were also unique thing for us because 90% of the projects were done using CNN (images classification and other stuff related to viewable out) . but over thing mostly different from others and we can work in both CNN and RNN together in a single project.

LITRATURE SURRVEY:

Understanding of a convolution neural network

The Networks he term Deep Learning or Deep Neural Network alludes to Artificial Neural (ANN) with multi layers. In the course of the most recent couple of decades, it has been viewed as a standout amongst the most amazing assets, and has turned out to be extremely mainstream in the writing as it can deal with an immense measure of information. The enthusiasm for having further concealed layers has as of late outperformed established techniques execution in various fields; particularly in example acknowledgment. A standout amongst the most well known profound neural systems is the Convolution Neural Network (CNN). It take this name from numerical direct activity between frameworks called convolution. CNN have various layers; including convolution layer, non-linearity layer, pooling layer and completely associated layer. The convolution and completely associated layers have parameters however pooling and non-linearity layers don't have parameters. The CNN has a great execution in machine learning issues. Exceptionally the applications that bargain with picture information.

LONG SHORT TERM MEMORY RECURRENT NEURAL NETWORK

Because of the development of data and correspondence procedures, sharing data through online has been expanded. Also, this prompts making the new included esteem. Accordingly, different online administrations were made. Be that as it may, as expanding association focuses to the web, the dangers of digital security have likewise been expanding. Interruption identification system(IDS) is one of the critical security issues today. In this paper, we develop an IDS display with profound learning approach. We apply Long Short Term Memory(LSTM) design to a Recurrent Neural Network(RNN) and train the IDS demonstrate utilizing KDD Cup 1999 dataset. Through the execution test, we affirm that the profound learning approach is successful for IDS.

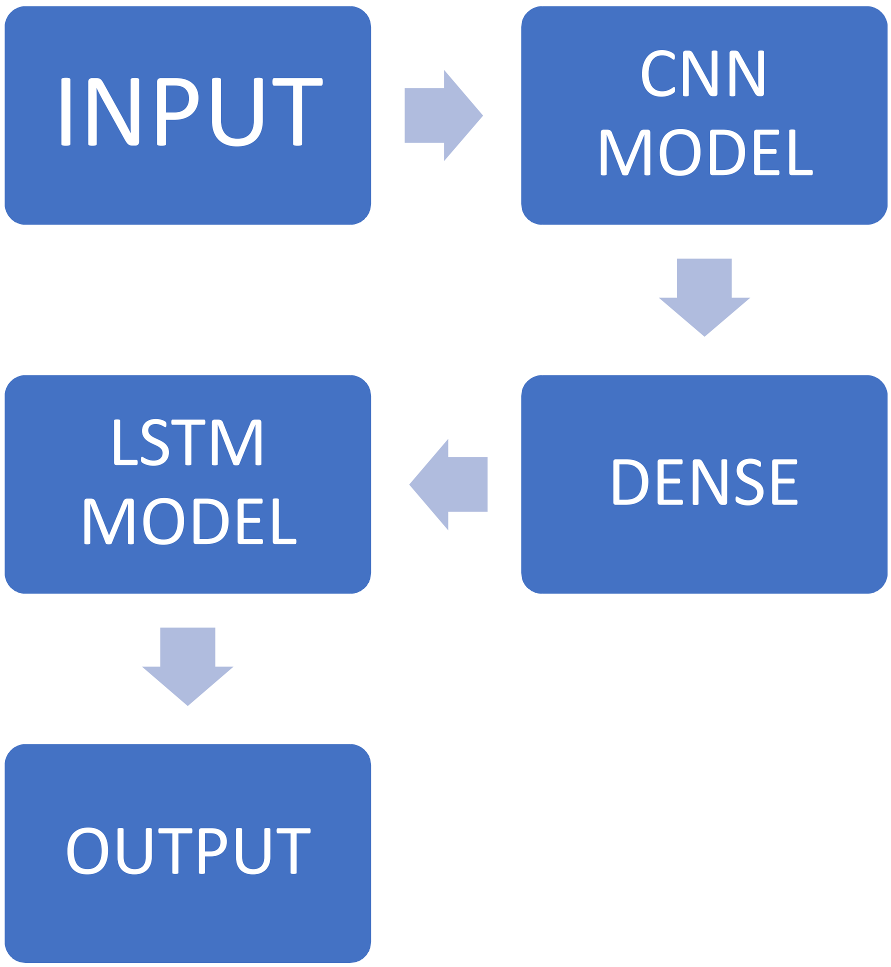
Time series analysis

Information exhibited in type of time arrangement as its examination and applications as of late have turned out to be progressively essential in various zones and spaces. In this paper brief review of some as of late critical standard issues, exercises and models fundamental for time arrangement examination and applications are exhibited. Paper likewise talks about some explicit pragmatic applications.

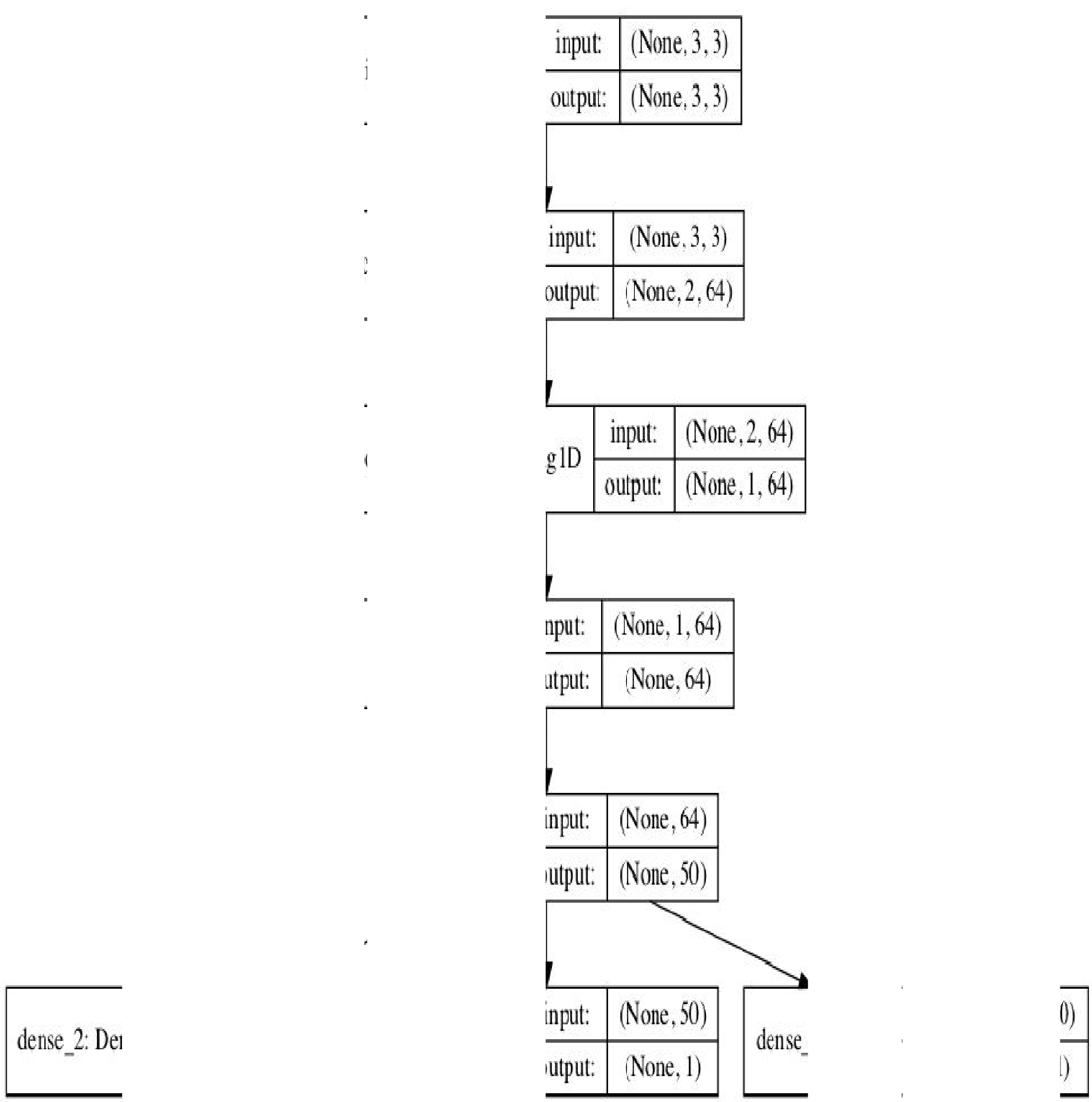
A SURVEY ON FORECASTING OF TIME SERIES DATA

Time arrangement examination and determining future qualities has been a noteworthy research center since years back. Time arrangement examination and anticipating in time arrangement information discovers it noteworthiness in numerous applications, for example, business, securities exchange and trade, climate, power request, cost and utilization of items, for example, fills, power, and so forth and in any sort of place that has explicit regular or popular changes with time. The anticipating of time arrangement information furnishes the association with helpful data that is fundamental for settling on imperative choices. In this paper, a nitty gritty study of the different procedures connected for anticipating distinctive sorts of time arrangement dataset is given. This overview covers the general estimating models, the calculations utilized inside the model and other enhancement methods utilized for better execution and precision. The different execution assessment parameters utilized for assessing the determining models are additionally examined in this paper. This investigation gives the peruser a thought regarding the different looks into that occur inside guaging utilizing the time arrangement information.

FLOW CHART:



DETAILED STRUCTURE:



DEMONSTRATION DETAILS:

DATASET:https://archive.ics.uci.edu/ml/datasets/individual+household+electric+power+consumption#

The above mentioned data set we taken for our project work .Which is in the text format.

The data set consist of 7 parameters global active power, global reactive power, intensity, voltage, sub metering 1,sub metering 2, sub metering 3and date and time .At first we are imported the necessary libraries. A 4^{th} sub metering variable can be created by subtracting the sum of three sub metering values from than total active power and multiple with 1000 and then divided by 60(minutes). We can use the read csv function load the data and combine the first two columns into a single date and time column then we can use as an index. We are using the raw dataset, there may a missing of values present in the given dataset . then given variable is float variable. For the missing values here we are using NaN values to restore the missing data .In Our project we are using both cnn and rnn models.

An extremely straightforward methodology is duplicate the perception from a similar time the day preceding. We can execute this in a capacity named fill missing() that will take the NumPy exhibit of the information and duplicate qualities from precisely 24 hours prior. We can utilize fill missing() specifically to the information inside the Data Frame. A model that makes utilization of different info factors might be alluded to as a multivariate multi-step time arrangement gauging model. A model of this sort could be useful inside the family unit in arranging consumptions. It could likewise be useful on the supply side for arranging power interest for an explicit family.

This surrounding of the dataset additionally proposes that it is helpful to down sample the per-minute perceptions of intensity utilization to every day sums. This isn't required, yet bodes well, given that we are keen on aggregate power every day. We can accomplish this effectively utilizing the resample() work on the pandas Data Frame. Calling this capacity with the contention 'D' permits the stacked information listed by date-time to be gathered by day. We would then be able to compute the whole of all perceptions for every day and make another dataset of day by day control utilization information for every one of the eight variables. The units of the aggregate power are kilowatts and it is valuable to have a blunder metric that was additionally in similar units. Both Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE) fit this bill, in spite of the fact that RMSE is all the more generally utilized and will be embraced in this instructional exercise. Dissimilar to MAE, RMSE is additionally rebuffing of figure errors. One conceivable score that could be utilized would be the RMSE over all gauge days. Running the evaluate forecasts() capacity will initially restore the general RMSE paying little heed to day, at that point a variety of RMSE scores for every day.

Train and Test Sets

The dataset consists of totally The information in a given dataset will be partitioned into standard weeks. These are weeks that start on a Sunday and end on a Saturday. The last year of the information is in 2010 and the principal Sunday for 2010 was January third. The information closes in mid November 2010 and the nearest last Saturday in the information is November twentieth. This gives 46 weeks of test information. Arranging the information into standard weeks gives 159 full standard weeks for preparing a prescient model l.The information in this arrangement would utilize the earlier standard week to foresee the following standard week.

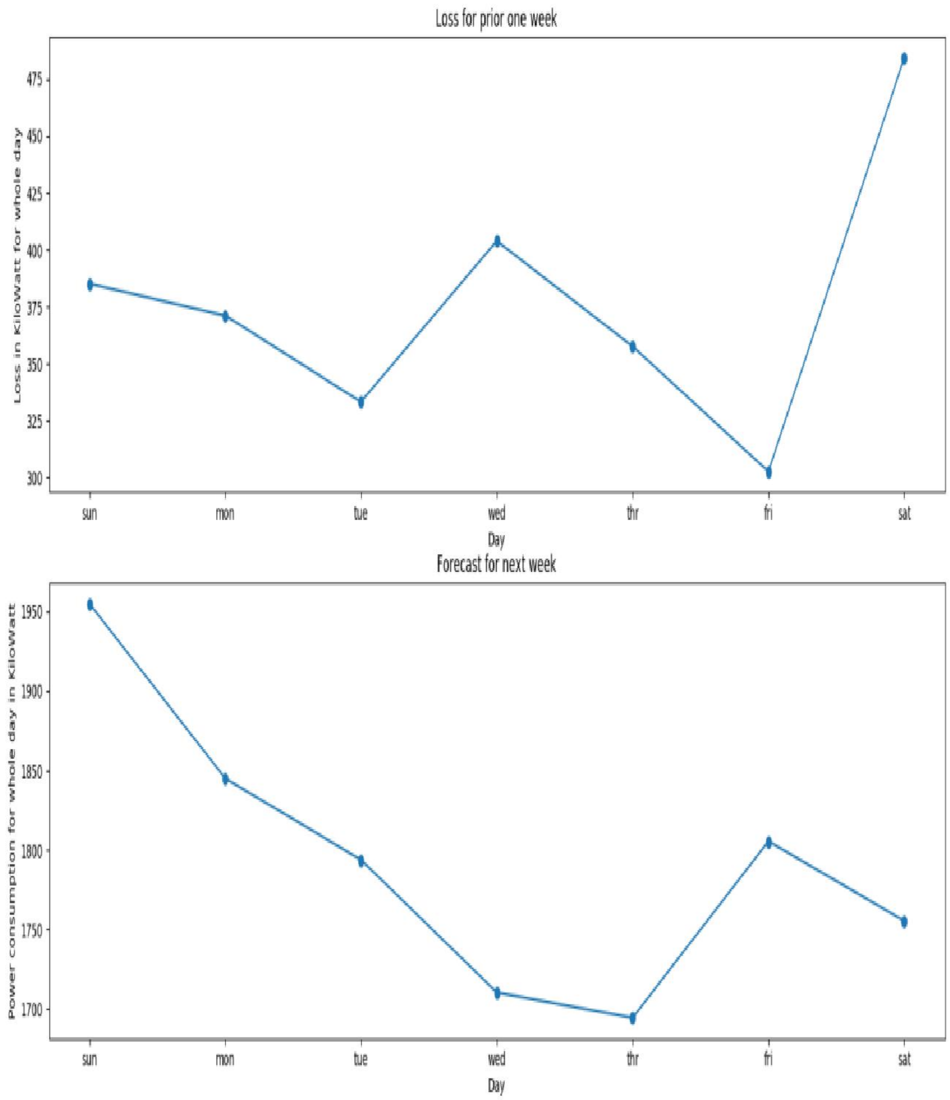
The preparation information is furnished in standard weeks with eight factors, explicitly in the shape [159, 7, 8]. We at that point need to emphasize over the time steps and gap the information into covering windows; every emphasis moves along one time step and predicts the ensuing seven days. When we run to supervised() work on the whole preparing dataset, we change 159 examples into 1,099; explicitly, the changed dataset has the shapes X=[1099, 7, 1] and y=[1099, 7]. Next, we can characterize and fit the LSTM show on the preparation information. This multi-step time arrangement determining issue is an auto regression. That implies it is likely best demonstrated where that the following seven days is some capacity of perceptions at earlier time steps. This and the generally little measure of information implies that a little model is required.

We will build up a model with a solitary shrouded LSTM layer with 200 units. The LSTM layer is trailed by a completely associated layer with 200 hubs that will translate the highlights learned by the LSTM layer. At long last, a yield layer will straightforwardly foresee a vector with seven components, one for every day in the yield grouping. Lastly we fit the model for 70 ages with a cluster size of 16.

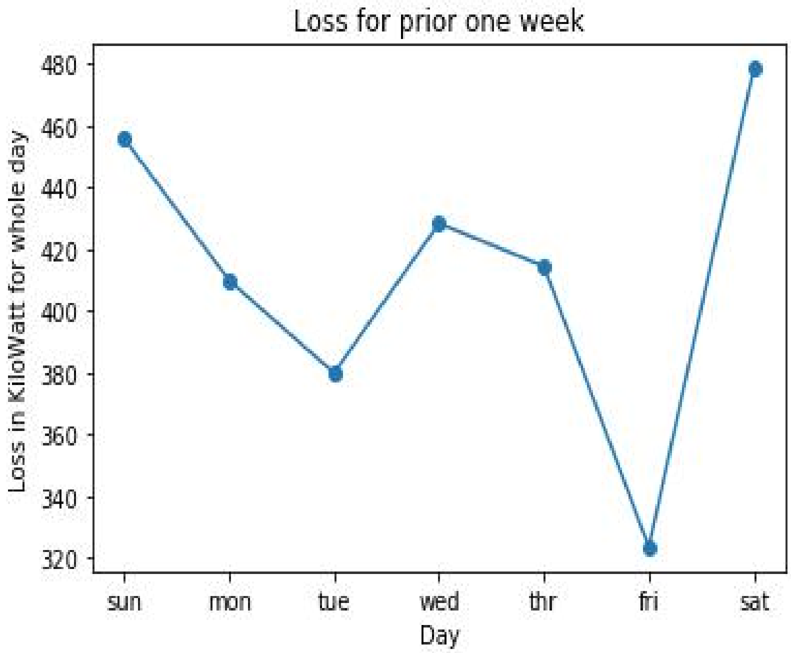
The estimate() work beneath actualizes this and takes as contentions the model fit on the preparation dataset, the historical backdrop of information watched up until now, and the quantity of information time steps expected by the model. Running the precedent fits the model and condenses the execution on the test dataset. A little experimentation demonstrated that utilizing two convolution layers made the model more steady than utilizing only a solitary layer. We can see that for this situation the model is apt, accomplishing a general RMSE score of around 367 kilowatts. A line plot of the per-day RMSE is likewise made.

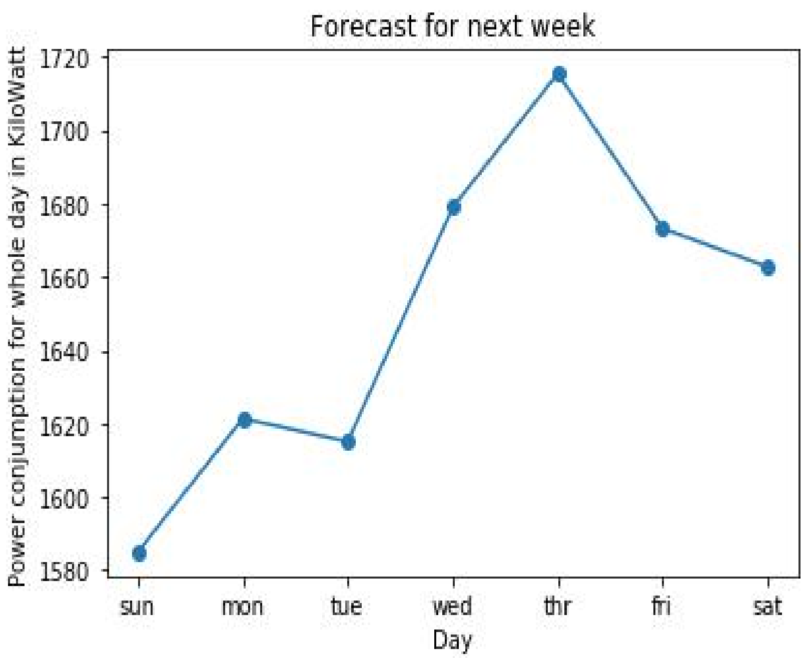
OUTPUT

FORCNN



FOR LSTM


Loss for prior one week
Loss in KiloWatt for whole day
480
460
440
420
400
380
360
340
320
sun
mon
tue
wed
thr
fri
sat
Day

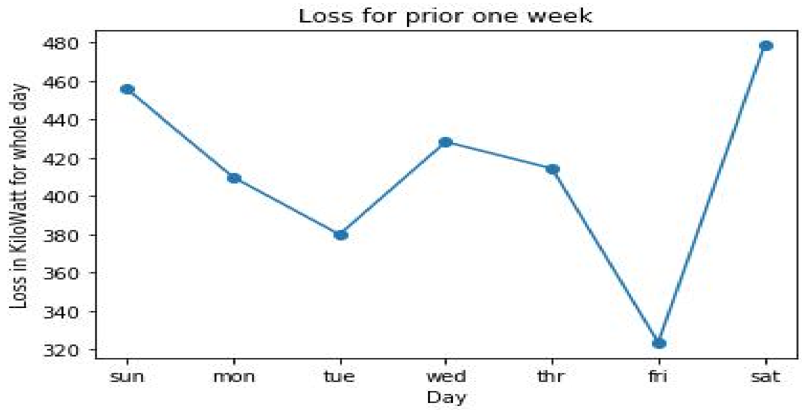

Forecast for next week
Power conjumption for whole day in KiloWatt
1720
1700
1680
1660
1640
1620
1600
1580
sun
mon
tue
wed
thr
fri
sat
Day

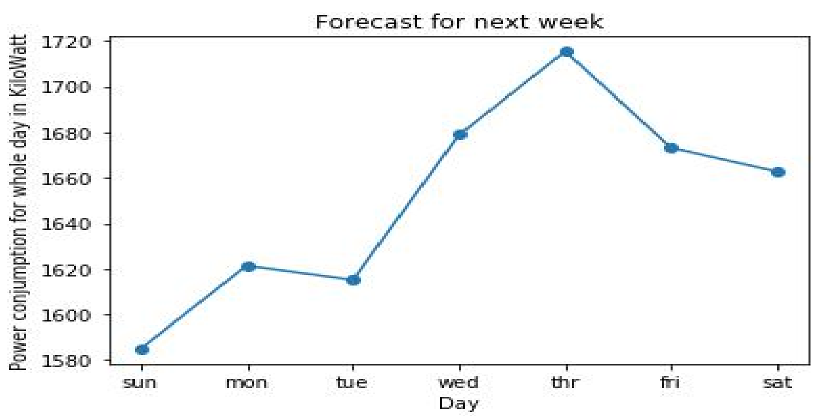
LIMITATIONS:

- ✓ In CNN model we are only able to give fixed length of inputs. To over this we used RNN model.
- ✓ We need maximum number of dataset to get good accuracy and for the prediction also.
- ✓ Since it is a raw dataset we require preprocessing each and every time and it requires some time to perform.

CONCLUSION:

From this project work we concluded that we forecasted the output for both models. In This project work analyzing which model is producing less loss and which day is minimum loss which is most precise for prediction.





FUTURE ENHANCEMENT:

We further built our model in a web page and application.

REFRENCE LINK :

DATASET:https://archive.ics.uci.edu/ml/datasets/individual+household+electric+power+consumption

FOR NEURAL NETWORKS

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7. https://www.analyticsvidhya.com/blog/2017/12/introduction-to-recurrent-neural-networks/

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GitHub Links:- https://github.com/Karthi-Mano/Household-Power-Forecasting

YouTube Video Links:-https://youtu.be/BKYUa11QcG4