**CT/DT Number:**

**Contestant Name:**

**College Name:**

Forecast energy usage of households- Forecast the electricity consumption of the top households with highest number of samples on an hourly basis based on the previous usage pattern. The major features for analysis includes ID, plans, date, time and meter readings in KWH.

**Background**

Today, the competitive energy market demands more accurate forecasting at different scales, ranging from a single smart-meter (end-user) up to a whole power grid system. As a result of this market need, load forecasting is considered today as an essential part of the electricity industry's planning process. Load forecasting is not only important for the management of electricity's generation, transmission, and distribution; but also, is crucial for consumers in order to optimize the use of their home electricity management systems.

**Your Understanding**

We consider each characteristic as an independent task and intend to predict multiple household characteristics simultaneously by designing a new multi-task learning formulation: Data was trained and the proposed model was validated using long short-term memory (LSTM) techniques. The model has been tested with actual energy consumption data and verified if this yields satisfactory performance.

**Scope**

Electrical load forecasting is an important process that can increase the efficiency and revenues for the electrical generating and distribution companies. It helps them to plan on their capacity and operations in order to reliably supply all consumers with the required energy.

* Availability of live data about the current power generation
* Device metadata, including the device’s generation capacity
* Historical data about weather and actual production recorded

**Out of Scope**

Forecasting energy demand is a complex task because it is affected by many variables at the micro level. Therefore, a macro model with only a few variables that can be predicted in a global way is needed; i. e. without a detailed analysis for each of these variables.

**Assumptions**

**General Assumptions:** We analyse that certain households consume more electric energy based on the usage of general appliances.

**Technical Assumptions:** We analyse LSTM is the best model for energy forecasting.

**Solution Approach**

We use two deep neural network architectures to energy disaggregation: Long short-term memory (LSTM); Long short-term memory (LSTM) is an artificial recurrent neural network (RNN) architecture used in the field of deep learning. Unlike standard feedforward neural networks, LSTM has feedback connections. A network which regresses the start time, end time and average power demand of each appliance called linear regression Algorithm. We use five metrics like ID, plans, date, time and meter readings to test the performance of these algorithms on real aggregate power data from households.

**Models/ Algorithms proposed**

Recurrent neural networks, or RNNs, are specifically designed to work, learn, and predict sequence data. A recurrent neural network is a neural network where the output of the network from one time step is provided as an input in the subsequent time step. This allows the model to make a decision as to what to predict based on both the input for the current time step and direct knowledge of what was output in the prior time step.

Perhaps the most successful and widely used RNN is the long short-term memory network, or LSTM for short. It is successful because it overcomes the challenges involved in training a recurrent neural network, resulting in stable models. In addition to harnessing the recurrent connection of the outputs from the prior time step, LSTMs also have an internal memory that operates like a local variable, allowing them to accumulate state over the input sequence.

**Implementation Framework**

**Software: Anaconda tool - Python 3.7**

**Solution Submission**

Share the link uploaded on GitHub.\\ <https://github.com/bhuvaneshwari09/bhuvi.git>

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