

Transmission Line Loss Determination of Electricity by Using Convolutional Neural Network

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Abstract—Businesses are concerned about energy losses. Electronic gadgets have become more prevalent as a result of their adoption. The frequency with which home electricity usage data is collected has grown, allowing for sophisticated data analysis that was previously unavailable. Indeed, adopting Smart Grid (SG) networks, which are freshly improved networks of linked devices, may considerably enhance the existing energy infrastructure's dependability, economy, and durability. The SG involves sharing a lot of data, including information on specific users' power use. And using this information, machine learning and deep learning algorithms may be able to detect power theft users reliably. This paper presented a Convolutional Neural Network (CNN)-based model for automated network-based vulnerability scanning that has excellent classification performance in many categories. Testing from iteration two to four iterations, this study examines research to discover the ideal configuration of the sequential model (SM) for categorization. The method is validated using a two-layer design, including an efficiency of 0.92, the whole first layer is composed of 128 nodes while the second level consists of 64 nodes. This allows for the development of a higher-level classifier for electrical signals, which may be employed in a number of applications. CNN was used to create electrical signal detectors, and SM was used to extract data from an electricity usage dataset. Furthermore, the number of features in the data set can be reduced using the Blue Monkey (BM) approach, and these results are then used to develop high-performance models. In this regard, the focus of this study has been on lowering the amount of needed features in the dataset in order to establish a rising classification algorithm for electrical signals. Experiments have applied the proposed systems' fantastic performance, with just 666 characteristics required to combine the CNN and BM methods. Comparative to 1035 traits when CNN was used alone. This shows that the CNN and BM models are better than the CNN model in terms of lowering sufficient know while maintaining the same reliability.

Keywords— Power Consumption, Deep Learning (DL), Convolutional Neural Network (CNN), Electricity consumption dataset

I. INTRODUCTION

Electric power grids are one of the most important and complex synthetic systems in modern life. The legacy energy system is being replaced with the transition to a power grid, thanks to new breakthroughs in monitoring, transmission, management, and sensors the phrase "smart grid" refers to the

dispersion of renewable and distributed energy sources in order to achieve flexibility, economy, and dependability identity, efficacy, and longevity. The concept of SG is being acknowledged via the use of fictitious architecture to hide the legacy power grid [1]. The cyber-infrastructure enables the collection and analysis of data from a wide range of scattered endpoints, such as phasor assessment devices, water meters, and circuit breakers.

Typically, these grids include certain enhancements that will increase the grid's reliability, effectiveness, and supply of a consistent source of electricity to homes and businesses. Furthermore, SG encompasses a wide range of clean energy sources (wind, solar, and other), as well as cloud processing [2–3]. "smart metering" refers to a smart electric instrument that calculates energy use statistics with more accuracy than a traditional meter and drives and acquires data through a two-way link [4]. As a result, advanced metering grids work with smart sensors, allowing corporations to control and regulate the SG using communication and knowledge technologies [5–7]. Electrical energy has become more important in human existence. Electrical energy losses occur often throughout the generation, distribution, and transfer of electrical energy. Failures (TLs) and semi losses (NTLs) are different types of losses.

Electrical energy losses are classified into nine types [8]. One of the most significant NTLs is energy fraud. Monitoring power theft is the subject of a vast number of studies. Conventional methods of detecting power theft include personally inspecting a faulty meter set up or disconfirmation, and linking abnormal measurements with the crime. Usual ones, and seeing a line along power's transition. These methods are ineffectual, expensive, and even time-consuming. The presence of SGs increases the likelihood of detecting cases of power theft. SGs are made up of traditional electricity networks, Computation systems that sense and administer networks, as well telecommunications grids that link smart devices in connections [9]. Smart networks connect service providers and employers by moving information and energy. Smart sensors or meters may gather a variety of data in this fashion, including connection state data, electric power use, financing information, and energy generation cost [10]. As a consequence, the focus of this thesis is on developing an effective approach to detect power theft in order to solve all of the aforementioned difficulties. To discover power pirates

and examine data on electricity usage. The CNN element, in particular, can capture the periodicity of power use data. To help in the identification of power theft, this model combines the strength of the CNN component with the BM algorithm [11].

This research's key research contributions may be seen as;

1. To analyze power theft with increasing connectivity, this paper provides a model using deep algorithm based on CNN and BM methods. It is the first research that we are aware of that proposes and For evaluating power theft in infrastructure networks, researchers tested a model employing a CNN deep algorithm model combined with the BM algorithm. 12 tests on a large, precise dataset of power use have been carried out on a large scale. Furthermore, the results of these tests suggest that our model (CNN & BM) beats a number of other models already in use. The proposed model has several merits, including the simplification of the novel knowledge brought via the CNN model and the accurateness in the detection electricity-theft.

II. LITERATURE REVIEW

In this section, a thorough literature review on some related issues of the Smart Grid (SG) is presented. Firstly, some critical works on SGs are mentioned. Secondly, a survey on electricity theft detection techniques is given. Then, some related works on deep neural networks are reviewed. Next, a survey on the deployment of (CNNs) for detection of electricity theft is given. Finally, the related work on the BM algorithm is introduced.

A. Smart Grids

Because electricity networks are so important to the national economy, public security, and security, data protection has recently become a major study topic. Though privacy and security flaws are constantly appearing in the procedures, grid innovations, and equipment used in the relevance of worries to system-level safety, the systems of energy, fears to privacy are not always totally recognized in SG metering grids, and threats or theft by facilities, following that, we describe recent survey works in this field, highlighting the significant contribution and distinguishing characteristics. These include various survey articles on privacy and security in the field of SG that have been displayed. In 2013, Baig and Amoudi classified the SG cyber-attacks and countermeasures through five categories: Supervisory Control and Data Acquisition (SCADA), Injection of Data and Replay Attacks, Smart Meter Attacks, Network-based Attacks, and Physical Layer Attacks [12], which affect home area systems, local networks, and large area grids.

B. Electricity Theft Detection (ETD)

The current methods are studied of electricity theft detection in the literature, Using meter reading information to monitor down dishonest customers. The observation of customer load profiles for signs of energy theft in traditional power networks has drawn scholars' attention to this topic.

In 2010, Nagi et al. applied a data removal technique alongside with Support Vector Machine (SVM) classifier to detect irregular manners [13]. The average daily consumption of consumers over two years was estimated, and the long-period trend in consumption of energy was utilized to detect deceitful consumers. Unexpected changes in the load curve may be detected using this approach. Furthermore, the

detection time is around two years. Convolutional Neural Networks and Deep Learning (CNNs) This subsection, presents a survey on some earlier work related to CNN's.

C. Blue Monkey Algorithm (BM)

This subsection highlights previous work related to the Blue Monkey (BM) algorithm. In 2019, M. Mahmood and B. Al-Khateeb introduced an A total of 43 well-known trial functions, which are often used in the planning field, are used to test the BM method [14]. A comparable functioning examination using Gravitational Search Algorithm (GSA), Artificial-Bee-Colony (ABC), Particle Swarm Optimization (PSO), and Biogeography-Based Optimizer was also used to confirm BM (BBO). The findings revealed that the BM method is only marginally related to metaheuristic algorithm selection. BM is also able to enter the global optimum despite efficiency challenges.

Electricity loss is a major issue that is being addressed by power companies all around the globe. Losses occur often throughout the administration, production, and transmission of energy. Non-technical and technical losses are the most common types of power losses. Power theft is among the most serious non-technical losses. Hacking the meter or bypassing it or manipulating with the meter reading are all examples of bad conduct. Energy theft may result in a heavy load of electrical schemes, flowing electricity, threats to public health and safety, and enormous revenue losses for the electricity company, such as electrical and fire shocks. According to the learning process of each methodology, there are three primary groups of methods for detecting quasi losses (NTLs): data-oriented methods, network-oriented methods, and hybrid approach. Nevertheless, ETD based on Deep Learning is the most prevalent and effective of these approaches.

In this section, the energy losses are typically categorized into either Non-technical losses (NTLs) or technical losses (TLs) have been discussed. Power theft is one of the primary factors of NTLs in the utility grid. The most prevalent approaches for detecting NTLs are described and split into three categories: network-oriented methods, data-oriented methods, and hybrid methods. Each category may be further subdivided into a variety of approaches. These procedures have been described. Following that, associated ETD concerns in AMI structures are investigated. In addition, DL and CNNs are briefly discussed. The BM algorithm has now been described.

III. PROPOSED METHOD

The suggested power protection detection algorithm is covered in this study in terms of format and execution. The systems are trained and tested using a realistic power usage dataset provided by China's State Grid Corporation. Using CNN-based deep learning and Blue Monkey methodologies, this research aims to detect energy theft from consumers' energy use patterns. This classifier model is developed in a supervised way by many stages using a dataset that contains daily power usage data from both regular and counterfeit customers. To train a model, the information is first preprocessed using a data preparation procedure. For greater speed, the preparation stage often includes creating fake data. The suggested model is then hyper-tuned before being assessed using testing data.

A. Electricity Usage Data

This study based on a set of real-world customer power use statistics provided by China's State Grid Corporation (SGCC). Table 1 shows the meta data information for this dataset. There are 1,035 columns and 42,372 rows in this collection. The first column has ID's of the customer, the second graph contains a "Flag" forecast reference, The days' columns begin with the third column and run all the way up to the fifth column (1,035). The dataset's meta data types are a collection of letters, integers, and non-numeric values that are absent or incorrect (NaN). For further than two years, the figures and incomplete or inaccurate data indicate the quantity of energy use (electricity signals) for each customer. Furthermore, the Meta data the column containing the flags are ones and zeros, indicating user type (either a thief or normal), where the number of ones in "Flag" column correspond to the number of thief users which are 3,615 thieves, while the zeros correspond to the normal electricity users which are 38,757 users. Finally, as indicated in table, the number (42,372) reflects power users' data on electricity consumption during a period of 1,035 days (from January 1, 2019 to October 31, 2021).

B. Power Stealing Detecting (Etd) Design Construction

The suggested Electricity Theft Detection model may be summarized as follows: the information is processed through many modification procedures to decrease it, and then the SM is built using Method. The third stage is to create a prediction model (ETD model), which may be accomplished in two ways. The first step is to use SM, as explain BM method is used for the major surgery. The input is a limited information Sequencing Theory, and the result is a framework of electricity theft identification with efficiency and cost, in which this approach uses a collection of fully - connected layer, pooling layer, to develop and then examine the power utilization data, as well as a soft max layer (dataset).

C. Proposed Algorithm (BM)

BM is expressed as follows that enhances the Electricity Theft Detection (ETD) template and returns the optimal placement option. The electrical theft detection (ETD) template is the inputs to this procedure. The Blue Monkey's behavior is imitated by the BM algorithmic software. BM is a collection of solutions for families and students, each with a unique values.

Algorithm (1): Steps of BM.

Input: Electricity theft detection (ETD) template.

Output: Best template of electricity theft detection (ETD) template with its accuracy and loss.

Step1: Generate random template for population of BM (Parents, Childs).

Step2: Generate rand (uniform random).

Step3: Initialize location of monkey (X) and power rate of monkey (rate) and weight of monkey (W), where (rate $\in [0, 1]$, W $\in [4, 6]$) for each solution (Parents and Childs).

Step4: Distribute the BM randomly into one team (t).

Step5: Calculate fitness for each solution (Parents, Childs).

Step6: For the Parents, select worst and best value of fitness and store it in currentbest, while Childs select the best fitness.

Step7: Set the number of iterations.

Step8: For I=1 to number of iterations, Execute Steps (9 to 14) for each solution.

Step9: Update rate, X location of all BM (Parents) by Equations (2.1 and 2.2).

Step10: Update rate, X location of Childs by Equations (2.3 and 2.4).

Step11: Update fitness for the (Parents, Childs).

Step12: Update current best.

Step13: If the best location of Childs is better than the best location of the Parents then the best solution = current best location of Childs, else best solution = current best location of Parents.

Step14: Return the optimal BM (Best solution in the population)

In Algorithm (1). This method receives a collection of options, each of which provides a pattern for lowering the information and ETD. There are ten answers in all, each extending up to length of 1035 producing random systems utilizing ones and zeros. This template will be used in two ways: first, it is being employed to create a table; second, it will the very initial step is to decrease the size of the used dataset using the alter function, which takes as input the BM pattern in addition to (in case of building model) original dataset. A smaller data set is resulted out of this operation. Then, using a fresh collection, present a system with an input that has equal shape characteristics equal to the size. When there is a fresh electrical signal, the next method is applied.

To categorize, the Electric Transmitter components must be reduced and use the same pattern, allowing the Energy Signals to be categorized to use this framework. The main purpose of constructing a BM model is to decrease the amount of characteristics in a collection.

The first step is to build SM using Algorithm (1). Then before building SM, the given dataset passed to several modify operations to reduce it. The next stage is to create a prediction model (ETD template), which may be done in two ways. SM is used for the initialization step. The BM method is used for the major way. The resulting template from BM is for enhance ETD Template and Features Reduction. The purpose of reduction process of dataset and features is to enhance the performance of prediction model. For classifying a new electricity signal, the electricity signal at first is converted to array, then reducing the data of this array using the same template used in building the prediction model by sending electricity signal array and template to modify function. The output of modify function is the electricity signal after reducing its dataset according to the template.

D. Calculating Accuracy Using Fitness Value

The input is dataset, and the output is accuracy. The fitness is calculated and will be used to modify the dataset to produce the reduced dataset. The reduced dataset will be used for train and test. The resulting values from fitness, train and test used to evaluate the accuracy.

IV. RESULTS AND DISCUSSION

The categorization of electricity signals, which has a broad number of different implications, is one of the world's most critical topics. The proposal is put to the test in this section, and the results are discussed to show the system's efficacy. The power consumption information was used in five different ways. The outcomes of the evaluation of the electrical signals classification setup are presented in the first section. The next section depicts the results of trying two layers (chosen from the previous portion) on a set of nodes and determining the optimum configuration. The third way shows the results of using BM method of two selected layers with the best configuration, while the fourth section shows the reliability and loss resulted from using BM model and CNN. The last part compares the CNN and BM models' damage and

reliability statistics with the CNN model's loss and accuracy outcomes. The tests were performed using the Python programming language on a Windows 7 PC with an AMD E2-1800 (1.70 GHz) CPU and (4.00 GB) RAM.

A. Research Using Classifiers Part Design

Various designs were used to evaluate the arrangement of completely linked levels in respect to number of nodes and layers, starting with 2 levels and finishing by 5 levels. Each layer has a large limit of 128 nodes and a base width of 16 nodes. Each row in Table (2) shows the whole model arrangements and what results that were derived from this model, whilst the columns reflect the following: The first column is the model number, which indicates the study's model series; the second column is the number of completely linked layers in the model, which runs from two to four levels; and the column is the amount of hidden nodes, which ranges from two to four layers (16-128). The fourth column gives the chosen architecture's highest accuracy. The fifth column provides the chosen architecture's poorest precision. The mean is shown in the sixth column. The model's precision the overall average loss is shown in the seventh column, and this number is equal to the difference between the actual and anticipated labels of the electrical signals during retraining, and is as little as feasible. The time spent on training is shown by the last column. Table (3) shows that the values of precision are convergent, indicating that the network is secure. In Table (2), The design with two layers was chosen since it offers the best average accuracy and the least amount of time spent. The results presented in Table (2) for two layers in details and shows how to find the accuracy; loss and the time spent in performing each operation as shown below.

Table 2. Presents the Parameters And Outcomes Of A System With Two To Four Nodes

NO	Layers	Nodes	Most Reliable	Lowest Reliability	Reliability Avg	Average Loss	Period Avg (Sec)
1	2	128-128	0.92	0.92	0.92	0.27	13.1
2	2	64-64	0.92	0.91	0.92	0.28	10
3	2	32-32	0.92	0.92	0.92	0.29	10
4	2	16-16	0.92	0.92	0.92	0.30	10
5	2	128-64	0.92	0.92	0.92	0.26	10
6	2	128-32	0.92	0.92	0.92	0.28	10
7	2	128-16	0.92	0.92	0.92	0.28	10
8	2	64-32	0.92	0.91	0.92	0.28	10.1
9	2	64-16	0.92	0.92	0.92	0.27	10
10	2	32-16	0.92	0.91	0.92	0.30	10
11	3	128-128-128	0.92	0.92	0.92	0.26	10
12	3	64-64-64	0.92	0.92	0.92	0.27	10.1
13	3	32-32-32	0.92	0.92	0.92	0.30	10
14	3	16-16-16	0.92	0.92	0.92	0.29	10
15	3	128-64-32	0.92	0.92	0.92	0.27	10.1
16	3	64-32-16	0.92	0.92	0.92	0.28	10
17	4	128-128-128-128	0.92	0.92	0.92	0.27	10
18	4	64-64-64-64	0.92	0.91	0.92	0.29	10.1
19	4	32-32-32-32	0.92	0.92	0.92	0.29	10
20	4	16-16-16-16	0.92	0.92	0.92	0.29	10
21	4	128-64-32-16	0.92	0.92	0.92	0.27	10

In table (3), ten training rounds (rows) the proposed model is presented. The columns are as follow: the first column represents the count of nodes contained in each layer, which are 128 as well as 128 nodes for the first and second layers respectively. The second column represents the number of training experiment. The third, fourth, and fifth columns contain the average loss, average accuracy and average time of every utilized model respectively, where the average loss is 0.26, and the average accuracy is 0.91, and the average time is equal to 13.1 seconds. The last two columns represent the worst and best accuracy for ten training rounds in which the worst accuracy is 0.91 and the best accuracy is 0.91.

Table 3. Model of Two Layers (128-128)

Nodes No.	Time	Loss	Accuracy	Train No.	Loss Avg	Accuracy Avg	Avg Period Sec
128-128	23	0.26	0.92	1	0.26	0.91	13.1
	24	0.26	0.92	2			
	11	0.25	0.92	3			
	11	0.26	0.92	4			
	11	0.28	0.92	5			
	10	0.28	0.92	6			
	11	0.27	0.92	7			
	10	0.25	0.92	8			
	10	0.29	0.92	9			
	10	0.27	0.92	10			

B. Using Bm In A CNN Model With The Best configuration Of Two Layers (128-64)

After experimenting with several classifier configurations (Completely Connected Layers), This setup was chosen to create the suggested classifiers (to decrease the features) in the most efficient way possible. BM is used to create a two-layer arrangement. The number of iterations (10 iterations) and the number of solutions (10 solutions) utilized in the BM template are shown in this paragraph. Table (4), which describes Iteration 1, has twenty rows that reflect the model's training cycles. This table's columns are as follows: For each training round, the first, second, third, and sixth columns reflect the model's sequence, losses, reliability, and duration, correspondingly. Where 0.27 is the average loss, 0.91 is the average predictability, and 10 seconds is the mean amount. The lowest accuracy is 0.91, while the precision value is 0.92.

Table 4: Iteration 1 of Two Layers Model (128-64) using BM

Model Number	Time	Loss	Accuracy	Loss Avg	Accuracy Avg	Avg Period Sec
1	10	0.26	0.92	0.27	0.91	13.1
2	10	0.30	0.92			
3	10	0.28	0.92			
4	10	0.27	0.92			
5	10	0.29	0.92			
6	10	0.30	0.91			
7	10	0.27	0.92			
8	10	0.26	0.92			
9	10	0.27	0.92			
10	10	0.26	0.92			
11	10	0.26	0.92			
12	10	0.34	0.92			
13	10	0.27	0.92			
14	10	0.27	0.92			
15	10	0.34	0.92			
16	10	0.25	0.92			

17	10	0.26	0.91
18	10	0.26	0.91
19	10	0.25	0.91
20	10	0.28	0.91

Table (5), which describes Iteration 2, has twenty rows that reflect the model's training rounds, with the same description as table (5), (4). The mean duration is 10 seconds, the average loss is 0.30, the average accuracy is 0.91, and the mean duration is 0.30. The poorest precision is 0.90, while the finest precision is 0.92.

Table 5: Iteration 2 of Two Layers Model (128-64) using BM

Model Number	Time	Loss	Accuracy	Loss Avg	Accuracy Avg	Avg Period Sec
1	10	0.26	0.92	0.30	0.91	10
2	10	0.26	0.92			
3	10	0.37	0.92			
4	10	0.37	0.92			
5	10	0.27	0.92			
6	10	0.27	0.92			
7	10	0.26	0.92			
8	10	0.27	0.92			
9	10	0.26	0.92			
10	10	0.26	0.92			
11	10	0.35	0.91			
12	10	0.26	0.92			
13	10	0.39	0.91			
14	10	0.30	0.92			
15	10	0.27	0.92			
16	10	0.50	0.92			
17	10	0.28	0.91			
18	10	0.26	0.92			
19	10	0.28	0.91			
20	10	0.26	0.92			

Table 6: Iteration 3 of Two Layers Model (128-64) using BM

Model Number	Time	Loss	Accuracy	Loss Avg	Accuracy Avg	Avg Period Sec
1	10	0.92	1	0.30	0.91	10
2	10	0.92	2			
3	10	0.92	3			
4	10	0.92	4			
5	10	0.92	5			
6	10	0.92	6			
7	10	0.92	7			
8	10	0.92	8			
9	10	0.92	9			
10	10	0.92	10			
11	10	0.92	11			
12	10	0.92	12			
13	10	0.92	13			
14	10	0.92	14			
15	10	0.92	15			
16	10	0.92	16			
17	10	0.92	17			
18	10	0.92	18			
19	10	0.92	19			
20	10	0.92	20			

C. Evaluation Of Our Proposed Method With Other Methods Regarding Loss And Accuracy

The below table (7) shows the evaluation of our proposed method with state of the art of the methods. Evaluation Of Our Proposed Method with Other Methods Regarding Loss and Accuracy (128-64).

Table 7: Evaluation of Our Proposed Method with Other Methods Regarding Loss and Accuracy (128-64)

Evaluation types	CNN	CNN & Blue Monkey (BM)
No. of Nodes	128-64	128-64
No. of Layers	2	2
Accuracy	0.92	0.92
Loss	0.26462948	0.265327107
time	10 seconds	8 seconds
Features	1035	666

Table (7) has three columns: the first column lists the names of the inputs and outputs, the second column lists the results of the CNN algorithm, and the third column lists the findings of the CNN algorithm combined with the BM method. While the rows of this table are as follow: the first row represents name of algorithms proposed in this study. The second row represents the number of nodes for each algorithm, where are used same nodes in both algorithms (128 and 64 nodes). The third row represents number of layers for each algorithm, which are two layers for both algorithms. The fourth row shows the accuracy ratio, where are the ratio obtained in both algorithms are (0.92). The fifth row shows the loss ratio, in which the result of the machine learning method is (0.26) and the outcome of the proposed method is (0.26) with (0.26). The period required implementing procedures is shown in the sixth row, with an average of 10 seconds for the CNN model and 8 seconds for the CNN and BM algorithms. The seventh row depicts the amount of features in both methods, with the result achieved using the Classification technique being (1035 feature) and the result acquired combining the CNN and BM algorithms being (1035 feature) (666 feature).

Moreover, it should be emphasized that proposed method models output forms the machine learning method in terms of decreasing sufficient know while maintaining the identical reliability. The biggest essential advantage of lowering functionality is that it may help save time. Furthermore, as developed to clarify, resulting may help in the process of removing characteristic inconsistencies.

D. Evaluation Of The Proposed Approach With Some Other

The results in Table (7) indicates that the suggested technique is better to other ways in terms of accuracy with a large number of customers (42372 customers) compared with the obtained accuracy and number of customers that are used by other methods.

Table 7: Evaluation of the proposed approach with some other approaches

Reference	Methods	Number of Consumers
[20]	(SVM)	36176
[21]	(CNN-LSTM)	17120
[22]	(SVM, OPF, C4,5 tree)	NA
[23]	Regression	30
[24]	SVM	36176

[25]	Fuzzy logic	NA
[26]	Fuzzy classification	NA
[27]	Neural networks (NN)	NA
[28]	Neuro-fuzzy	4159
[29]	CNN	12,180
Present	CNN, BM	42372

V. CONCLUSION

Through the results obtained, the following conclusions can be made; i-A Machine learning approaches outperform other methods as they employ classified data to learn models with high accuracy. Where using labels in electricity consumption dataset made the building of models has high performance, ii- By lowering the dataset as indicated in section 3, the reliability of model construction and new electrical signal classification is improved, iii-Increasing fully connected layers and nodes in each layer lead to increasing the delay, without much affecting the accuracy, in the models in term of training and classifying. The following are some of the most significant findings: The method is divided into two layers, each with 128 and 64 components. The final loss resulting from this model is 0.26 and the final accuracy resulting from this model is 0.91 with an amount of time 8 seconds. In addition, the features were (1035 feature) before using BM algorithm, while become (666 feature) after using BM algorithm. In future work, there is still room to improve the results accuracy through implementing our methods with wide convolutional neural network. And, Combining CNN with LSTM can, in theory, help achieving better results in terms of accuracy and efficiency.

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