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Convolutional Neural Network for Voltage Stability Prediction in Power System Operation

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ABSTRACT

It is desirable for power system operators to maintain healthy power system operation. Increase in load demand will stress a power system, hence demands voltage stability study to be conducted to plan further mitigation action. Established voltage stability assessment methods requires long computational time despite of providing accurate results. To address this issue, Convolutional Neural Network (CNN) is implemented to predict the voltage stability of IEEE 26-bus Reliability Test System based on the load demand in the system. Experimental work on the proposed study has indicated that CNN is capable of producing predicted outputs with low prediction error indicated by low value of Root Mean Square Error (RMSE). Comparative studies with respect to Artificial Neural Network (ANN) and Support Vector Machine (SVM) indicates CNN can predict outputs with lower RMSE value compare to ANN and SVM, which highlights the superiority of CNN in producing better prediction. The results of this study can benefit power system operators to assess the voltage stability of the system with faster computational time, hence speeding up mitigation actions when required.

Key words : Convolutional Neural Network, Fast Voltage Stability Index, Root Mean Square Error, Voltage Stability.

1. INTRODUCTION

Maintaining a healthy power system operation is very important. As a power system is stressed with an increase in load demand, voltage stability study is required to assess the performance of the system [1]. The importance of power system stability study is also highlighted by [2]. Fast estimation of voltage stability is required for online applications so that appropriate corrective measures can be taken to avoid voltage collapse [3].

Chakrabarti *et al*. [4] has conducted a study on the implementation of Artificial Neural Network (ANN) for on-line voltage stability monitoring application. The neural network is trained using both active and reactive power flow in the transmission lines at different loading level of New England 39-bus power system as the input data while the output data is taken from the available active power margin for each loading level. In [5], Sharma *et al*. has conducted a study on the implementation of ANN to assess the voltage stability index of several power system models. The voltage stability is assessed and indicated by Global Voltage Stability Margin (GVSM). The input data fed to the ANN is taken from the active and reactive loads from the power system while the output data is taken from the value of GVSM at each loading condition. In this study, no feature reduction process is conducted in the study.

Nakawiro *et al*. [6] has conducted a study on the implementation of ANN to monitor voltage stability in a power system. The data used to train the ANN model is generated by using random values with range of 60% up to 120% of the base case active and reactive load demand while maintaining constant power factor. The output data for the neural network are voltage stability information which comprises from Voltage Collapse Proximity Index (VCPI), L-Index, Power Transfer Stability Index (PTSI), Power based Voltage Stability Margin (PVSM) and minimum singular value. Feature reduction using Principal Component Analysis (PCA) is also conducted to eliminate repetitive and choosing data with maximum information about the data set used. In a different study, Shah *et al*. [7] has conducted a study on the implementation of ANN to monitor the voltage stability of New England 39-bus system. The input data are obtained from the measured voltage magnitude and voltage angle from the Phasor Measurement Unit (PMU) which is installed in several location in the power system. The output data is taken from several voltage stability index such as Voltage Profile Index (VPI), Fast Voltage Stability Index (FVSI), Line Stability Index (LSI), and Line Stability Factor (LSF). In the study, 4 model of ANN has been developed with the same input data to cater for 4 different voltage stability indices as mention previously.

In [8], Shukra *et al*. has conducted a study on the implementation of Support Vector Machine (SVM) for voltage stability monitoring in power distribution system. In this study, random value of active and reactive load ranging from base case value up to 130% of base case load value are used as the input data for the SVM. In this study, Voltage

Security Margin (VSM) is used as the voltage stability indicator. The VSM value obtained from each loading condition is also used as the output data for the SVM. In the study, the hyperparameters of SVM is also optimized using Particle Swarm Optimization (PSO) and Genetic Algorithm (GA), resulting in SVM model optimized with PSO produce better results compared to SVM model optimized by GA.

In recent years, Convolutional Neural Network (CNN) has gained interest from researcher in various research fields. CNN is categorized as a part of deep learning, which is a subset of machine learning family under artificial intelligence domain [9]. Majority studies conducted related to CNN focuses on classification problem especially image recognition. For example, CNN has been widely applied in dentistry field for dental image diagnostics which has been review by Schwendicke *et al*. [10]. Meyer *et al*. [9] has conducted a survey on the application of CNN for radiotherapy procedure. In the survey conducted, application of CNN and deep learning approaches used in the radiotherapy workflow has been extensively reviewed. A study conducted by Kumar *et al*. [11] has applied CNN for segmentation and classification of brain tumor using images obtained from Magnetic Resonance Imaging (MRI) process. In the study, the neural network used is a variant of CNN termed as Deep CNN with integration of Dolphin Echolocation based Sine Cosine Algorithm (Dolphin-SCA). The segmentation process in the study will be performed using a fuzzy deformable fusion model with Dolphin-SCA. In a different study, Byra *et al*. [12] has proposed a CNN-based neural network termed as Selective Kernel U-Net Convolutional Neural Network (SK-U-Net) for breast mass segmentation in Ultrasound imaging. In [13], Jain *et al*. has conducted a study about the implementation of CNN to detect pneumonia by using x-ray images. The possible output class from the study is divided into pneumonia and non-pneumonia. In [13], 6 different models of CNN where 2 of the models are developed by the authors which consists of 2 and 3 convolutional layers respectively. For the latter 4 CNN models, the authors implemented transfer learning on VGG16, VGG19, ResNet50 and Inception-v3 models.

Several studies are also conducted in the domain of electrical engineering related to the implementation of CNN. In [14], Watanabe *et al*. has implemented CNN to classify a series of Scanning Acoustic Microscopy (SAM) images into 2 different classes, namely “normal device” and “abnormal device”. An area of interest (AOI) is extracted from the images obtained from SAM. Then, the extracted image will be fed into the classifier. Authors in [14] also mentioned that since the number of sample image is small, data augmentation process is required by rotation and mirroring the images, hence the number of image samples can be increased. In [15], Plathottam *et al*. has implemented CNN to solve multi-class multi-label classification problem. The input data used to train and test the proposed CNN model is obtained from 24-hour wind power generation and load data from Midcontinent ISO. The CNN will be used to classify 3 different output features for each data sample, which are wind power strength, wind power variability and wind power load share. Further studies conducted about the implementation of CNN for power system transient stability have been demonstrated in [16] and [17].

While several works proposed to predict voltage stability in power system has been established, these approaches is hampered by long computational time required due to repetitive power flow computation despite of providing complete and accurate results [6]. Hence, this paper presents the implementation of Convolutional Neural Network (CNN) to predict static voltage stability index value of a power transmission system. The input data used during training, validation and testing process are obtained from the active and reactive load values in the power system. To achieve the stated aim, the neural network model will be trained for regression problem. The remainder of the paper is organized as follows. The performance of CNN in predicting the voltage stability index value of a power system is measured by using the value of Root Mean Square Error (RMSE) determined by comparing the predicted output of testing dataset compared to its actual output. Comparative studies of CNN with respect to ANN and SVM is conducted to observe and compare the performance of CNN, ANN and SVM in predicting the voltage stability index value in terms of RMSE value for each algorithm.

In the next section, methodology used in this study will be discussed in terms of data preparation and processing as well as neural network architecture design. Next, the prediction performance of CNN is analyzed and assessed in terms of predicting the value of voltage stability index in the power system. Finally, a conclusion is drawn based on the finding obtained from the study.

2. METHODOLOGY

This section describes the methodology used in this paper. The first section is presenting brief discussion on the voltage stability index used for voltage stability assessment. Next section describes the steps taken for dataset preparation. In later section, the architecture of CNN model and the formulation used to assess the prediction performance of CNN are presented.

2.1. Voltage Stability Assessment

In this study, the voltage stability prediction will be conducted and tested on a power transmission model known as

IEEE 26-bus Reliability Test System (RTS). The IEEE 26-bus RTS is a power transmission model consists of 26 buses with 23 load center. A graphical representation of IEEE 26-bus RTS is illustrated as in Figure 1.

To assess the voltage stability of IEEE 26-bus RTS, a static voltage stability index used in the study is Fast Voltage Stability Index (FVSI), and it is mathematically expressed as (1). In this paper, the voltage stability of the power transmission system will be indicated by the value of the highest FVSI of IEEE 26-bus RTS, and it is represented as in (2) [18].

$$FVSI_{ab} = \frac{4Z_{ab}^{2}Q_{b}}{V_{a}^{2}X_{ab}} \quad (1)$$

$$FVSI_{\max} = \max\left(FVSI\right) \quad (2)$$

In (1), $FVSI_{ab}$ is defined as the FVSI value for the transmission line connecting a^{th} bus to the b^{th} bus of the IEEE 26-bus RTS. The reactive power flowing into b^{th} bus is denoted Q_b while the voltage at a^{th} bus is indicated by V_a. The magnitude of impedance and reactance of the transmission line connection a^{th} bus to b^{th} bus is indicated by Z_{ab} and X_{ab} respectively. In (2), $FVSI_{\max}$ is defined as the highest value of FVSI in the power system, while the function max($FVSI$) is defined as a function to determine the maximum value of FVSI among the FVSI values of all transmission lines in the IEEE 26-bus RTS.

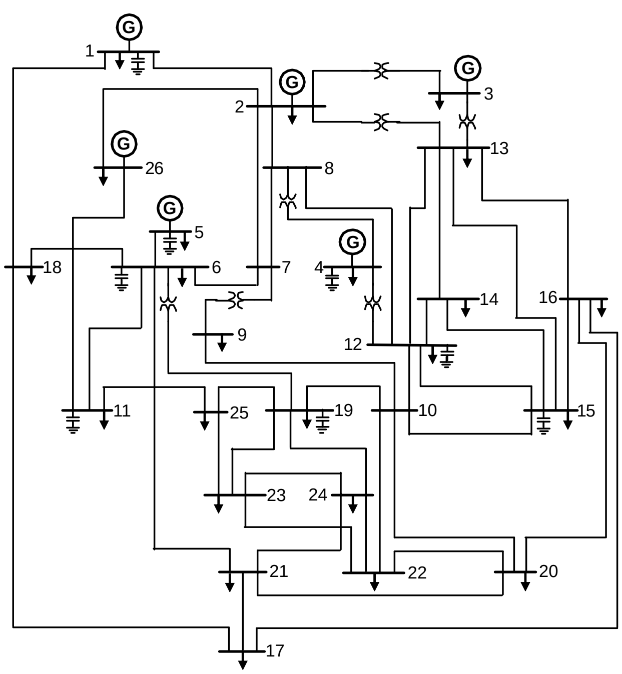

Figure 1: Single line diagram of IEEE 26-bus RTS

2.2. Dataset Preparation

In order to train the neural network, a set of data needs to be prepared. The process of preparing the dataset to be used in this study is visually represented by Figure 2. The first stage of acquiring the dataset is to gather the required information from the power system network. In this study, the required input data is the value of active and reactive loads at all buses. However, the active and reactive load information for buses 7, 8, and 10 are excluded from the data acquisition since buses 7, 8, and 10 has no load connected to the bus. To simulate the data acquisition process, the active and reactive load demand values are randomly generated, and power flow analysis was solved. Upon solving the load flow analysis, the value of $FVSI_{\max}$ is determined. The obtained data is arranged in 2 rows where the first row lists the value of active loads while the second row lists the value of reactive loads. The arrangement of the data is illustrated as in Figure 3.

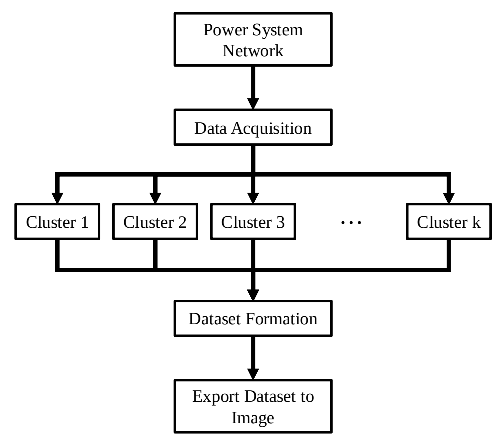

Figure 2: Process of obtaining dataset for neural network training

P_d	1	2	3	4	5	6	9	11	…	25	26
Q_d	1	2	3	4	5	6	9	11	…	25	26

Figure 3: Illustration of data arrangement

For each loading condition, a value of $FVSI_{\max}$ is obtained. Then, the data is segmented in different cluster based on the value of the $FVSI_{\max}$. The clustering category of $FVSI_{\max}$ is represented as in Table 1.

Table 1: Clustering category of $FVSI_{\max}$

Cluster	Information
Cluster 1	$FVSI_{\max} < 0.4$
Cluster 2	$0.4 \le FVSI_{\max} < 0.5$
Cluster 3	$0.5 \le FVSI_{\max} < 0.6$
Cluster 4	$0.6 \le FVSI_{\max} < 0.7$
Cluster 5	$0.7 \le FVSI_{\max} < 0.8$
Cluster 6	$FVSI_{\max} \ge 0.8$

The process of acquiring data is continued by generating more data with even distribution of data generated across all cluster categories. Then, the dataset will be formed. The number of data to be gathered in the dataset to be formed will comprise datasets for training, validation, and testing process. The data will be chosen from each cluster and the number of data chosen for each cluster should be kept even across all clusters if possible.

Then, the information from the dataset will be exported to image form, which then will be fed to the neural network. The process of exporting the dataset into image is discussed as follows. Firstly, a set of data will be loaded. The arrangement of the data is as shown in Figure 3. Then, a surface plot is generated from the loaded data. A sample of generated surface plot is illustrated as in Figure 4. It should be noted that all the axes of the surface plot should be removed from the plot.

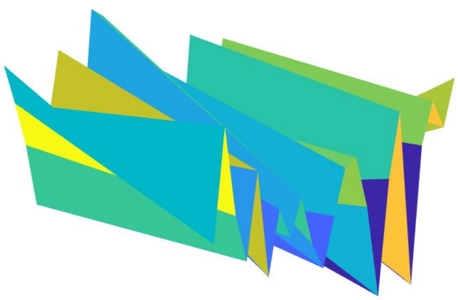

Figure 4: A sample of surface plot generated from the loaded data

After the plot has been generated, the image size is then reduced to 50 by 50 pixel, and the color is transformed to greyscale. This step is taken in order to reduce the computational burden of the neural network during its training and validation process. The transformed image from Figure 4 is illustrated by Figure 5. Note that the image in Figure 5 has been enlarged for the purpose of clarity in this paper.

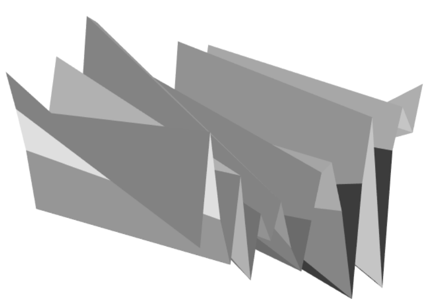

Figure 5: Sample of surface plot transformed to greyscale

The greyscale image is then saved as the input data for the neural network. The process repeats for other sets of data until all the data in the dataset produced during dataset formation process have been converted to image.

2.3. Prediction Performance Assessment

In order to assess the performance of prediction produced by the CNN model, the error between the predicted output compared to the targeted output of testing dataset is evaluated by using Root Mean Square Error (RMSE) value. The mathematical expression of RMSE is presented as in (3).

$$RMSE = \sqrt{\sum_{i=1}^{n} \frac{\left(y_{p,i} - y_{t,i}\right)^2}{n}} \quad (3)$$

where *RMSE* is the root mean square error value, *n* is defined as the number of observation (in the case of this paper, number of data in the testing dataset), $y_{p,i}$ and $y_{t,i}$ are defined as the predicted output and targeted output for i^{th} observation respectively [19].

2.4. Training and Testing of Neural Network

Before the machine learning algorithm is trained, the dataset generated in previous process is loaded. The dataset generated is made up of 3 pool of datasets, namely training dataset, validation dataset and testing dataset. For CNN and ANN, the neural network is trained using the training dataset and validation dataset will be used for validation process during the training process. In the case of SVM, the model will be trained using the combination of the said training and validation datasets combined. For all CNN, ANN and SVM, after these models are trained, testing datasets will be fed to the models to assess the prediction accuracy of CNN, ANN and SVM. Upon feeding the testing dataset to the CNN, ANN and SVM models, a set of predicted output will be produced. The results of predicted output are then compared with the targeted output of the testing dataset and the RMSE value is computed. The RMSE values for CNN, ANN and SVM are then compared. Model with a lower RMSE value is considered as a better model since a model with a lower RMSE value indicates that the model is able to do prediction with lower error. The process of training and testing the neural network is graphically illustrated as in Figure 6.

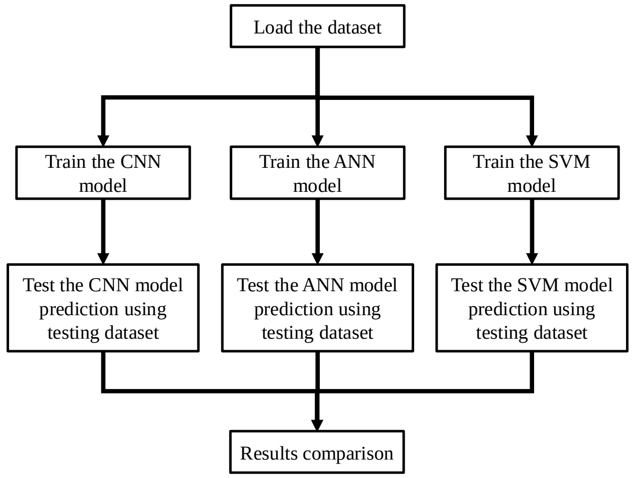

Figure 6: Training and testing process of CNN, ANN and SVM models

2.5. Architecture of Convolutional Neural Network

In this study, CNN is implemented to solve regression problem of predicting voltage stability of IEEE 26-bus RTS. The CNN developed for this study comprises of 1 image input layer, 2 stages of layers in which that a stage of layer having 1 convolutional layer, 1 ReLu layer, 1 max pooling layer and 1 batch normalization layer. After the 2 stage layers, a fully connected layer is introduced, followed by a batch normalization layer and a regression output layer. The CNN architecture used in this study can be graphically represented as in Figure 7.

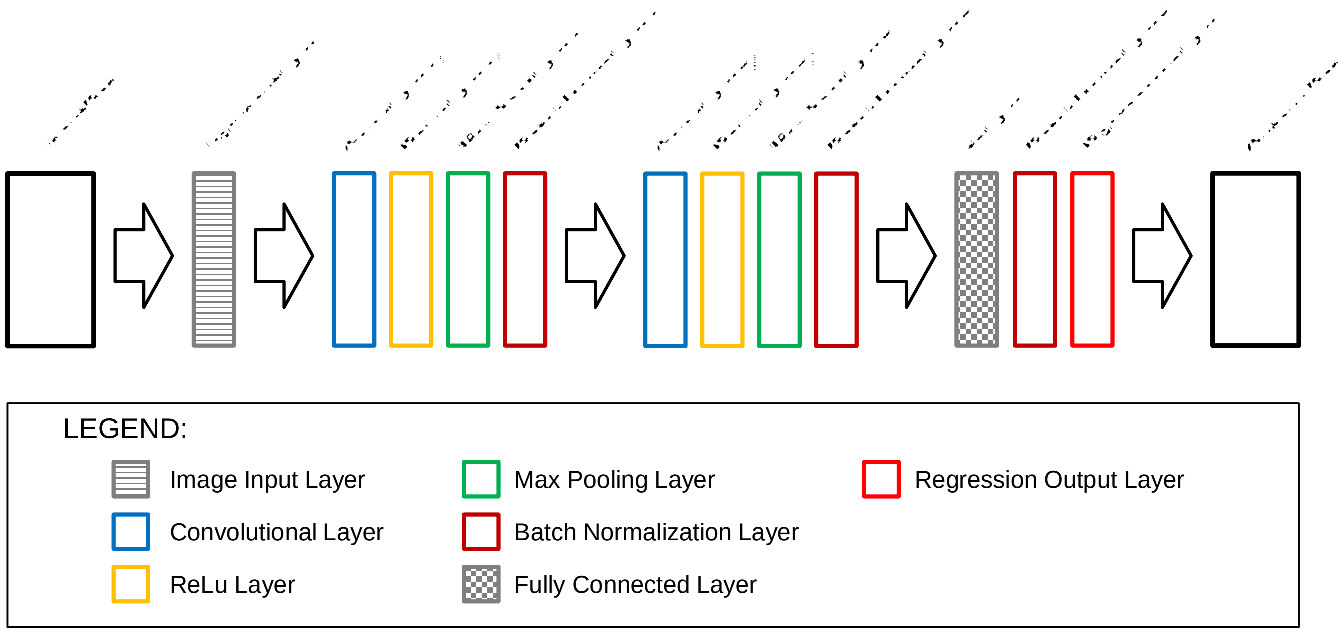

Figure 7: CNN architecture used in this study

3. RESULTS AND DISCUSSION

The effectiveness of CNN in predicting voltage stability index value is tested on IEEE 26-bus RTS. The CNN is trained and tested using a dataset with 1000 data samples which includes training, validation, and testing dataset. Among the 1000 data, 75% of data are allocated for training dataset, 10% of the data are allocated for validation dataset and the remaining 15% of the data are allocated for testing dataset. The proposed CNN and other machine learning algorithms used in this study are developed using MATLAB software.

Table 2: Parameters of CNN used in this study

Parameter	Value
Number of filters for *ConvLayer1*	1
Size of filter for *ConvLayer1*	25 by 25
Pool size for *MaxPoolLayer1*	5 by 5
Pool stride for *MaxPoolLayer1*	1 by 1
Number of filters for *ConvLayer2*	1
Size of filter for *ConvLayer2*	1 by 1
Pool size for *MaxPoolLayer2*	1 by 1
Pool stride for *MaxPoolLayer2*	1 by 1
Training solver name	Stochastic Gradient Descent with Momentum
Learning rate	0.001
Momentum	0.85
Validation Frequency	10
Validation Patience	5
Maximum Epoch	100

Prior to machine learning model training, several parameters are required to be set. The hyperparameters for CNN model is listed in Table 2. For performance comparison purpose, the same dataset is used to train ANN and SVM models. The parameters for ANN and SVM are listed as in Table 3 and Table 4 respectively.

Table 3: Parameters of ANN used in this study

Parameter	Value
Training algorithm	Levenberg-Marquardt
Neuron number in 1st hidden layer	7
Activation function for 1st hidden layer	Hyperbolic Tangent Sigmoid
Neuron number in 2nd hidden layer	5
Activation function for 2nd hidden layer	Hyperbolic Tangent Sigmoid
Neuron number in output layer	1
Activation function for output layer	Linear
Training accuracy	1×10^{-3}
Maximum Epoch	100

Table 4: Parameters of SVM used in this study

Parameter	Value
Kernel function	Linear
Box constraint	1
Solver	Sequential Minimal Optimization (SMO)
Other parameters are set to their default values	

To observe the variation of results, each model (CNN, ANN and SVM) will be trained and tested for 10 times with 10 different datasets. For each dataset, it will be fed into CNN, ANN and SVM for training and testing process. The RMSE value obtained from the testing process for each model is computed using (3) and recorded in Table 5.

Table 5: Results of RMSE value of testing dataset over 10 runs

Run	RMSE value of testing dataset		
	CNN	ANN	SVM
1	0.1489	0.2298	0.2310
2	0.1366	0.2217	0.2304
3	0.1380	0.2301	0.2178
4	0.1310	0.1887	0.2015
5	0.1368	0.2217	0.2304
6	0.1632	0.2072	0.2178
7	0.1333	0.1812	0.2201
8	0.1309	0.2208	0.2164
9	0.1312	0.2208	0.2164
10	0.1311	0.2208	0.2164

From the results obtained and documented in Table 5, it can be observed that for every run of training and testing process of CNN, ANN and SVM, CNN has recorded better performance in terms of lower RMSE value of the testing datasets compared to ANN and SVM. At 8th run of training and testing process, CNN has recorded the lowest RMSE value compared to other runs. The highest RMSE value for the testing dataset obtained by CNN is at 0.1632 which is on the 6th run of the training and testing process. However, the value is lower compared to the 6th run on ANN and SVM.

On the other hand, ANN has indicated better performance in predicting the voltage stability index value compared to the SVM in most run of the training and testing process. The prediction performance of ANN has surpassed SVM in 9 of the 10 runs, with exception of run 3 where SVM indicates better RMSE value compared to ANN. From the 10 runs conducted, ANN has managed to record the lowest RMSE value of testing dataset at 0.1812. The highest RMSE value recorded by ANN is at 0.2301. For the case of SVM, the lowest RMSE value recorded is at 0.2015, which is during run number 4. At run 1, SVM has recorded the highest RMSE value of the testing dataset which is at 0.2310.

Therefore, it can be deducted that CNN is capable of making predictions with lower error which have been indicated by low value of RMSE. Because the datasets used to train, validate, and test the algorithms is in image form, it is clear that CNN has done a better job in making generalization of the data fed to the network during training and validation process. This results also support the claim that CNN is great at image recognition task which is mentioned by [20][21].

CONCLUSION

This paper presents the implementation of Convolutional Neural Network in predicting voltage stability in a power system. Existing voltage stability analysis methods can provide accurate results, but these methods require long computational time to be performed. To alleviate the issue, machine learning algorithms are employed to predict voltage stability of IEEE 26-bus RTS based on the input data given in terms of active and reactive load demand in the power system. From the results obtained, it is evident that CNN has been able to predict the voltage stability index value of IEEE 26-bus RTS based on the input given to the neural network with low prediction error. Performance comparison of CNN with respect to ANN and SVM has revealed the superiority of CNN in producing better voltage stability index prediction indicated by lower RMSE value of testing dataset compared to ANN and SVM. Future work on the assessment of effects of dataset preprocessing as well as implementation of colored dataset instead of greyscale dataset on the prediction error reduction may be feasible to achieve a better voltage stability prediction using CNN.

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