



NETWORK RESOURCE MANAGEMENT THROUGH MACHINE LEARNING USING 5G

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Abstract: Classification (TC) systems enable the generation of the traffic under consideration. Deep Learning (DL)-based TC algorithms have surpassed older methods in complicated and current circumstances, even when traffic is encrypted. The majority of works on TC assume traffic flows on a wired network managed by the same network management domain. This assumption limits the capability of TC systems in wireless networks since undetected traffic transmissions from users in other network domains or identified ones with no traffic context in a shared spectrum can negatively effect users' traffic on one network domain. To address this issue, we present a unique method for achieving TC at any tier of the radio network stack. We suggest a spectrum-based approach.

Key Words: : Deep Learning, Convolution neural network, Framework, TC

1.INTRODUCTION This service has recently been upgraded with Machine Learning (ML) approaches to do automatic network traffic analysis such as network state forecasts, anomaly detection, virus detection, and traffic classification (TC). Using TC as an example, this network management job can infer the application that is generating the traffic. Knowing the traffic class allows you to apply precise security and QOS policies to the examined traffic. Several methodologies have been established and refined over the years to track the progress of technologies that drive the development of user applications and communication protocols. In complex and current circumstances, DL-based traffic classifiers have lately surpassed classic methods such as port-based classifiers, Deep Packet Inspection (DPI), and flow-based traffic analysis utilizing statistical ML, even when the traffic is noisy.

2. Problem Identification

The problem statement for RUL prediction is developed, and the theoretical foundations of CNN and RNN are introduced. To overcome the limitations of standard networks, a unique architecture known as CNN and RNN is built, and lastly, the details of deep architecture based on deep learning and the best transmission prediction processes are described. The primary goal is to implement the deep learning algorithm. To improve performance analysis.

3.PROPOSED METHODOLOGY

In the proposed system the baseline RNN architecture is inspired by fine-tuning and optimization stages based on the dataset supplied in this paper. Used a similar method as with the CNN to determine the optimum model by varying the number of recurrent layers as well as the type and number of recurrent units.

The number of recurrent layers was varied from one to four, with three recurrent layers producing the greatest results also experimented with different types of recurrent units, including GRU and LSTM, and found that GRU performed similarly to or better than LSTM in terms of execution time and accuracy in all of our trials. This observation is also consistent with earlier findings

4. System Design

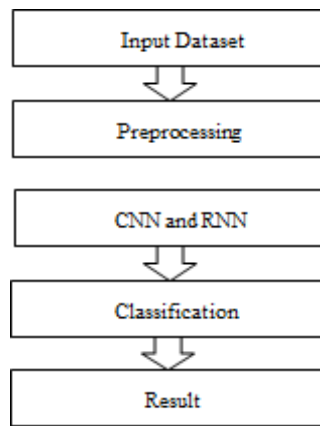


Figure 4.1 Flow diagram

Figure shows that first we have to give the input data set then Preprocessing the data and then classify the data using CNN&RNN algorithm finally we get the result.

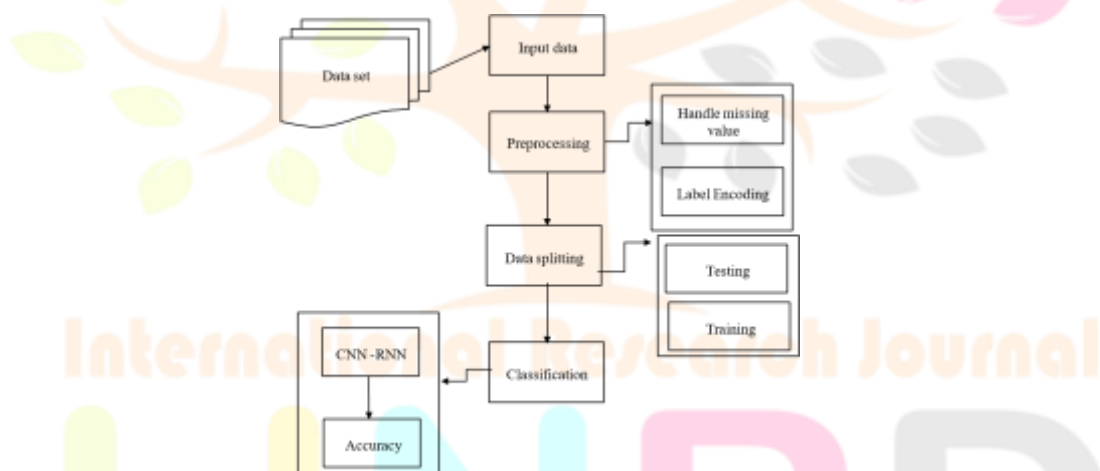


Figure 4.2 System Architecture

This show that we first we have to give the input data set then preprocessing the data. In preprocessing we have to perform two operation such as missing values, label encoding and then classify the data using CNN&RNN algorithm finally we get the result

5. Modules

In this project, we are using the following modules,

- Data selection
- Data preprocessing
- Data splitting
- CNN and RNN
- Deep learning

5.1 Data Selection:

- The dataset was collected from the dataset repository.
- In this step, we have to load the data with the help of pandas packages.

5.2 Deep Learning (DL):

- Use the ANN algorithm in the classification step to improve performance.

5.3 CNN:

- Convolution layers are made up of a collection of learnable filters (a patch in the image above). Every filter has a tiny width and height, as well as the same depth as the input volume (3 if the input layer is an image).
- For example, if we have to run convolution on an image with dimension $34 \times 34 \times 3$. The possible size of filters can be $a \times a \times 3$, where „a“ can be 3, 5, 7, etc but small as compared to image dimension.
- During the forward pass, we slide each filter across the whole input volume step by step (each step is called stride and can have a value of 2 or 3 or even 4 for high dimensional images) and compute the dot product between the weights of the filters and the patch from the input volume.

5.4 RNN:

The network is given a single time step of the input.

- Then, given the current input and the previous state, compute its current state.
- For the next time step, the current h_t becomes h_{t-1} .
- Depending on the difficulty, one can proceed through as many time steps as necessary to link the information from all prior states.
- The final current state is utilized to determine the output when all time steps have been finished.
- The output is then compared to the goal output, and an error is created.
- The error is then back-propagated to the network in order to update the weights, resulting in the network (RNN) becoming 7.4.

5.5 Output Testing:

Following validation testing, the next step is to question the user about the format necessary testing of the proposed system, as no system can be used if it does not produce the required output in the specific format. The output displayed or created by the system under examination. In this case, the output format is regarded in two ways. The first is in screen format, while the second is in printed format. The output format on the screen is verified to be correct because it was designed during the system phase based on the demands of the user. The hardcopy output also meets the user's specifications. As a result, the output testing yields no connection in the system.

5.6 Data Splitting:

Data splitting is the process of dividing available data into two parts, typically for cross-validation purposes.

- One portion of the data is used to create a predictive model, while the other is utilized to assess the model's performance.
- Part of analyzing data mining models is separating data into training and testing sets
- When you divide a data set into a training set and a testing set, the majority of the data is used for training and a smaller amount is utilized for testing.

6.Result and Discussion

Using the collaborative filtering process, the recommend Movie for a specific user id.

- Based on the overall categorization and forecast, the Final Result will be generated.
- The proposed approach's performance is assessed using metrics such as accuracy.

The capacity of a classifier is referred to as its accuracy. It properly predicts the class label, and predictor accuracy refers to how effectively a given predictor can anticipate the value of a predicted attribute for incoming data.

$$AC = \frac{TP+TN}{TP+TN+FP+FN}$$

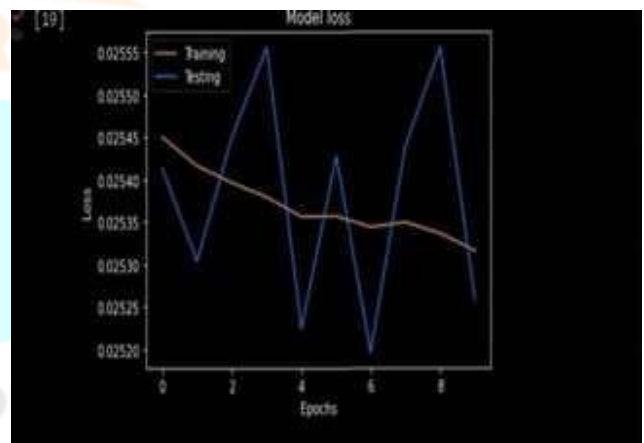
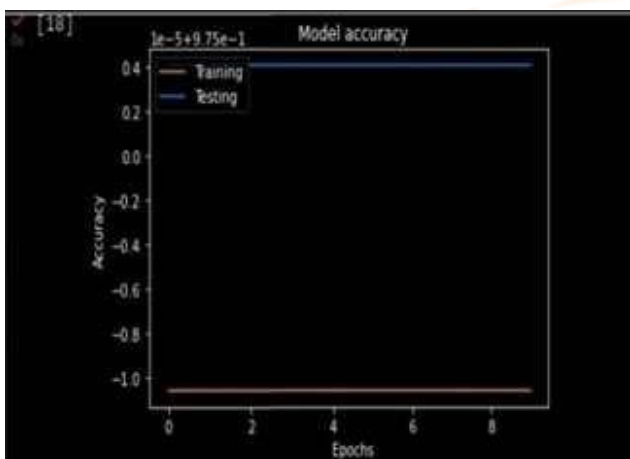
7. SOFTWARE TESTING STRATEGIES TESTING:

After the culmination of black box testing software is completed assembly as a package interface in errors have been discovered and corrected and the final series of software validation tests begin validation testing can be defined in a variety of ways, but a single definition is that validation succeeds when the software functions in a way that the customer can reasonably expect.

7.1USER ACCEPTANCE TESTING:

User acceptance of the system is critical to the

system's success. The system under consideration is tested for user acceptance by maintaining ongoing contact with the prospective system during the development of updates as needed.



```
[11]
=====
Total params: 81
Trainable params: 81
Non-trainable params: 0

None
Epoch 1/5
2194/2194 [=====] - 30s 3m/step - loss: 0.8907 - acc: 0.8704
Epoch 2/5
2194/2194 [=====] - 30s 3m/step - loss: 0.8284 - acc: 0.8708
Epoch 3/5
2194/2194 [=====] - 30s 3m/step - loss: 0.8258 - acc: 0.8708
Epoch 4/5
2194/2194 [=====] - 30s 3m/step - loss: 0.8236 - acc: 0.8708
Epoch 5/5
2194/2194 [=====] - 30s 3m/step - loss: 0.8251 - acc: 0.8708
 keras.callbacks.History at 0x7f4001018040

[12] model.compile(optimizer='adam', metrics=['acc'])
```

```
History = model.Fit(x_train, y_train, validation_data=(x_test, y_test), epochs=50, batch_size=64)
-----
Epoch 1/10
1894/1894 [=====] - 4s 4m/step - loss: 0.8257 - acc: 0.8708 - val_loss: 0.8254 - val_acc: 0.8708
Epoch 2/10
1894/1894 [=====] - 4s 4m/step - loss: 0.8254 - acc: 0.8708 - val_loss: 0.8251 - val_acc: 0.8708
Epoch 3/10
1894/1894 [=====] - 5s 5m/step - loss: 0.8254 - acc: 0.8708 - val_loss: 0.8254 - val_acc: 0.8708
Epoch 4/10
1894/1894 [=====] - 5s 5m/step - loss: 0.8254 - acc: 0.8708 - val_loss: 0.8256 - val_acc: 0.8708
Epoch 5/10
1894/1894 [=====] - 4s 4m/step - loss: 0.8254 - acc: 0.8708 - val_loss: 0.8256 - val_acc: 0.8708
Epoch 6/10
1894/1894 [=====] - 4s 4m/step - loss: 0.8254 - acc: 0.8708 - val_loss: 0.8251 - val_acc: 0.8708
Epoch 7/10
1894/1894 [=====] - 4s 4m/step - loss: 0.8254 - acc: 0.8708 - val_loss: 0.8254 - val_acc: 0.8708
Epoch 8/10
1894/1894 [=====] - 4s 4m/step - loss: 0.8251 - acc: 0.8708 - val_loss: 0.8254 - val_acc: 0.8708
Epoch 9/10
1894/1894 [=====] - 4s 4m/step - loss: 0.8251 - acc: 0.8708 - val_loss: 0.8256 - val_acc: 0.8708
Epoch 10/10
1894/1894 [=====] - 4s 4m/step - loss: 0.8251 - acc: 0.8708 - val_loss: 0.8256 - val_acc: 0.8708
CPU times: user 47.1 s, sys: 1.76 s, total: 48.8 s
Wall time: 41.4 s
```

8.CONCLUSION

Performance analyses revealed that the DL model based on CNN could obtain the greatest performance on the three specified tasks, with task accuracy distinguishing between classes above 99.9% in task 1, 97.8% in task 2, and 92% in task 3. When compared to byte-based DL models, these results are highly promising, with spectrum-based models achieving equal accuracy on task 1, a loss of 1.38% in task 2, and 4.37% in task 3.

Finally the suggested DL architecture can forecast a given class in the order of microseconds, which is attractive for integrating into spectrum-based real-time traffic analysers. Several issues must be addressed in future work with the proposed framework and the spectrum-based method for TC.

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