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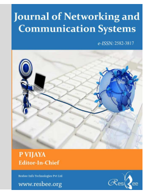

Base Station Transceiver Network Monitoring and Prediction Model Using Deep Neural Network for Enhanced Network Performance and Quality of Service

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Abstract: This paper presents an innovative deep neural network (DNN)-based approach for the real-time surveillance and failure prognostication of Base Transceiver Station (BTS) networks. The model utilizes historical network performance metrics such as call setup success rate, handover success rate, cell availability, percentage traffic channel, call drop rate, and power availability to forecast BTS network failures with an impressive accuracy prediction of 99.8%. In contrast to conventional methods that are often labor-intensive, this paradigm delivers scalable and efficient predictions, thereby facilitating proactive management of the network. The findings underscore the model's capability to enhance the quality of service by providing timely insights into the operational health of the network. By mitigating the shortcomings inherent in traditional systems, the proposed DNN model represents a significant advancement in telecommunications monitoring and management.

Keywords: Machine Learning, Deep Neural Network, Base Transceiver Station, Quality of Service, Network Failure Prediction.

Nomenclature

Abbreviation	Expansion
BTS	Base Transceiver Station
DNN	Deep Neural Network
PA	Power Availability
CA	Cell Availability
CSSR	Call Setup Success Rate
HOSR	Handover Success Rate
DCR	Drop Call Rate
PTTCH	Percentage Traffic Channel
SLA	Service Level Agreement
QoS	quality of service
ML	Machine learning
MSE	Mean Squared Error
MAE	Mean Absolute Error
ANN	Artificial Neural Network
PC	Problem Classification
KPIs	Key Performance Indicators
RE	Relative Error
GPU	Graphical Processing Units
APIs	Application Programming Interfaces
URLLC	Ultra-Reliable, Low-Latency Communication

1. Introduction

The telecommunications sector, along with its associated services, has undergone considerable transformation over the last twenty years, propelled by technological innovations and their contemporary applications [1]. Notwithstanding these advancements, the performance monitoring and management of BTS networks continue to encounter substantial obstacles, particularly within developing nations.

Conventional network management systems are increasingly challenged by the growing necessity for real-time monitoring and the substantial volume of network data, frequently impeding prompt decision-making. This paper advocates for a solution based on DNN to forecast BTS network failures by utilizing historical network performance data. In doing so, it aspires to enhance network dependability and QoS, equipping network operators with the requisite tools for proactive management and informed decision-making [2] [3]. The rest of the paper is organized as follows: Section 2 covers the literature review, Section 3 explains the Proposed Design Considerations, Section 4 mentions the Model, Normalization, and Problem Classification, Section 5 covers the Experiment and Results, Section 6 explains the advantage and disadvantages of the proposed method. Section 7 concludes the paper.

2. Literature Review

The use of ML in mitigating and resolving challenges faced within telecommunication networks has proven to be effective over the years, especially in the areas of fault prediction, traffic forecasting, and resource management. [4]

introduced a sophisticated six-layer data mining framework employing K-means and FIST algorithms for customer segmentation and fault identification. Despite its efficacy in problem classification, the model used synthetic datasets and conventional techniques, thereby constraining its scalability and relevance to real-time applications.

In 2023, Zhao et al. [5] augmented the predictive precision of base station traffic via their multi-model fusion approach that amalgamates Gradient Boosting, XGBoost, LightGBM, and MLP models. This ensemble learning framework yielded a decrease in MSE by 9.8% and MAE by 4.3%. Nevertheless, although their study highlighted the merits of ensemble learning, it was confined to traffic forecasting and did not incorporate real-time fault prediction or performance metrics specific to BTS.

The paper [6] and [7] utilized ML methodologies for data rate prediction and long-term mobile traffic forecasting, respectively, thereby illustrating the potential of ML to enhance network performance. However, these inquiries did not address the exigent challenges associated with real-time performance monitoring of BTS or proactive prediction of failures.

Although the extant literature elucidates the significance of ML within telecommunication networks, a salient gap persists regarding the application of ML for real-time monitoring of BTS and failure prediction. Current methodologies predominantly concentrate on overarching network optimization or traffic forecasting, failing to furnish actionable, real-time insights pertinent to the management of BTS.

2.1 Comparison of Proposed Model with Existing Methods

Table 1. *Comparison of Proposed Model with Existing Methods*

Method / Model	Technique Used	Dataset Characteristics	Key Strengths	Limitations	Accuracy (%)
Mondal & Barua (2018) [4]	K-means and FIST for fault detection	Synthetic datasets, six-layer architecture	Effective segmentation and fault classification	Lacks scalability, untested in real-time scenarios	Not Quantified
Zhao et al. (2023) [5]	Multi-model fusion (Gradient Boosting, XGBoost, etc.)	Real-world data, traffic-focused	High prediction accuracy for traffic forecasting	Limited to traffic prediction; no fault detection	90.2
Rihijärvi & Mähönen (2018) [6]	ML for data rate prediction	Real-world data, wireless networks	Improved resource allocation	Not designed for BTS monitoring or fault prediction	Not Quantified
Zhang & Patras (2018) [7]	Deep spatio-temporal neural networks for traffic	Long-term mobile traffic dataset	Captures temporal dependencies	Focused only on traffic; lacks real-time application	Not Quantified
Jamsheed et al. (2024) [8]	ANN for Network traffic Prediction	No specific dataset details are provided.	High prediction accuracy for traffic forecasting	Focused only on link traffic; lacks real-time application	98.1
Proposed DNN Model	DNN for fault prediction	861,755 real-world entries for BTS performance	Real-time prediction, high scalability, proactive insights	Requires live testing in operational BTS environments	99.8

2.2 Research Gap

While ML has been employed across various dimensions of telecommunication networks, its application for real-time performance monitoring of BTS remains insufficiently explored. For example, [5] improved the accuracy of traffic prediction yet neglected to tackle fault analysis or real-time operational challenges.

Similarly, [4] offered valuable insights into fault detection but were reliant on antiquated techniques and synthetic datasets, thereby restricting their practical implementation in dynamic settings.

This paper seeks to bridge this gap by proposing a DNN model specifically designed for real-time performance monitoring of BTS and proactive fault prediction. By harnessing advanced ML methodologies, the model aspires to provide precise, actionable insights, augment the accuracy of fault prediction, and facilitate efficient network management within contemporary telecommunication systems.

3. Proposed Design Considerations

To develop a monitoring and prediction system for BTS network failure, a DNN algorithm was employed. The following subsections discuss the various aspects of the model that was implemented.

3.1 System Model Architecture

The DNN architecture is composed of an input layer comprising six neurons, three hidden layers containing 24 neurons, and an output layer featuring a neuron designated for classification purposes. The configuration of the input layer is congruent with the number of features, thereby effectively assimilating pertinent data. The incorporation of three hidden layers was strategically chosen to augment model accuracy, while the selection of 24 neurons serves to strike a balance between complexity, reduction of overfitting, and assurance of robustness. An increase in the number of neurons beyond 31 did not yield any meaningful enhancement in accuracy. The solitary neuron within the output layer guarantees the establishment of clear decision boundaries for the six performance classifications, thereby facilitating precise predictive outcomes.

The training involved exploring batch sizes of 32 to 256. Larger batches accelerated training but needed more memory, while smaller batches improved generalization but slowed training. The ideal batch size considered dataset characteristics and computational resources. Training epochs ranged from 10 to 100. Each epoch represents a full pass through the dataset for learning. Monitoring is vital to balance epochs and over-fitting, as more epochs enhance convergence but may lead to over-fitting. See Fig. 1.

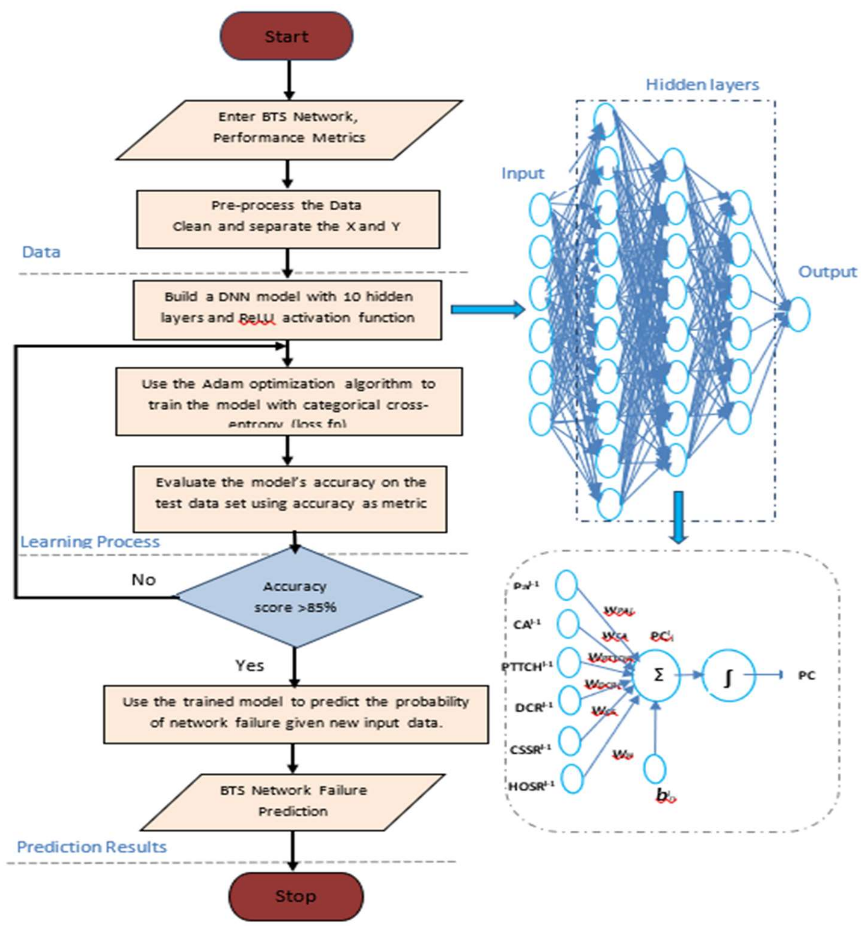

Fig. 1. Flowchart of DNN Architecture

3.2 Loss Function and Target Representation

For multi-class classification, the Categorical Cross-Entropy loss function was utilized. This loss penalizes low probabilities assigned to the true class labels, encouraging the model to assign higher probabilities to the correct classes.

The target variable, referred to as PC in this study, represents six distinct classes corresponding to BTS performance levels ranging from Excellent to Worst. These classes were encoded as integers from 0 to 5 using a label encoder, with each integer uniquely representing a performance category. This encoding facilitated efficient computation of the loss by aligning the encoded target labels with the model's output probabilities during training.

$$CCE = -\frac{1}{N}\sum_{i=1}^{N}\sum_{c=1}^{C} 1_{yi} \in C_c \log\left(p_{model}\left[y_i \in C_c\right]\right) \tag{1}$$

Equation (1) represents the Cross-Entropy Loss (CCE) for a DNN. It measures the dissimilarity between predicted probabilities (P_{model}) and true labels (y_i). Burstiness arises from summations and perplexity from logarithms, capturing complexity and unpredictability in the model's output.

3.3 Regularization

Dropout regularization at a rate of 0.2 was implemented during training to prevent over-fitting. The random dropping of neurons in the hidden layers promoted generalized learning. Dropout was not applied during testing or prediction to leverage all available neurons for accurate predictions.

3.4 Model Optimization

The Adaptive Moment Estimation (Adam) optimization algorithm was used with a learning rate of 0.001 for better convergence.

3.5 Data Gathering and Preprocessing

The dataset for this study consisted of 861,754 entries, spanning two years of real-time BTS network performance data sourced from one of the mobile network operators in Nigeria. Data was extracted in CSV format using MAPS and Affectli database management systems, with Excel and Python utilized for data transformation, analysis, and ML model development.

KPIs critical to BTS network failure prediction such as power availability, cell availability, PTTCH, DCR, CSSR, and HOSR were carefully selected. These KPIs were identified through correlation analysis, which highlighted their significant influence on the QoS and their direct role in determining network reliability and fault patterns. For instance:

- **Power Availability:** Impacts overall network uptime and service delivery.
- **DCR and CSSR:** Indicate call reliability and setup success, directly linked to user experience [10].
- **HOSR**: Reflects the seamless transfer of calls between cells, crucial for mobility [11] [12].
- **PTTCH and Cell Availability:** Represent network traffic capacity and service accessibility [13] [14].

The raw data underwent cleaning, with missing values replaced by the mean of each feature to maintain data integrity. Feature scaling was applied to normalize the diverse value ranges, ensuring unbiased learning by the model [15].

The dataset was split into training (70%), validation (20%), and testing (10%) subsets. Performance levels for each KPI were categorized based on mobile network operator standards. The preprocessed and normalized dataset was then fed into the DNN model, ensuring accurate and reliable BTS network failure predictions.

3.6 Training the DNN Model

Based on the size of the dataset, the complexity of the model, and the attributes of the BTS network performance metrics employed, the focus was to adopt an approach that ensures the robustness and reliability of the analyses ([16] [17]). To this end, a randomized splitting technique to allocate the dataset, adhering to a ratio of 70:20:10 for training, cross-validation, and testing respectively was used. The model was trained on the training dataset using different batch sizes and epochs. A repetitive process of training and cross-validation led to selecting a batch size of 256 and 100 epochs as the best configuration.

3.7 Evaluating the Model

The model's accuracy, usefulness, and reliability were evaluated by comparing predicted values with known values derived from manual classification. This comprehensive assessment affirmed the strength and effectiveness of the model.

3.8 BTS Network Failure Prediction

The final trained model was utilized to predict the probability of BTS network failure based on new input data containing relevant feature values.

4. Model, Normalization, and Problem Classification

In this paper, the data analysis focuses on the mathematical relationships and equations used in the ML predictive models for predicting BTS network failures. The mathematical model for the feed-forward neural network with one hidden layer is given by:

$$y = f\left(w_2 * f\left(w_1 * x + b_1\right) + b_2\right) \tag{2}$$

Equation (2) represents a neural network model with two layers. It applies weights (w_1, w_2) and biases (b_1, b_2) to input (x), employing activation functions (f) for non-linearity and complexity, enabling the network to make intricate predictions. Where y is the predicted value, x is the input feature vector, w_1, and w2 are weight matrices for the input and hidden layer, b_1 and b_2 are bias vectors for the input and hidden layer, f() is the activation function (e.g., ReLU). For a feed-forward DNN with six input features and ten hidden layers, the mathematical equation is:

$$y = f\left(w_{10} * f\left(w_9 * f\left(w_8 * ... * f\left(w_2 * f\left(w_1 * x + b_1\right) + b_2\right) + ...\right) + b_9\right) + b_{10}\right) \tag{3}$$

The bias term in a neural network is represented as:

$$z = w_1 * x_1 + w_2 * x_2 + ... + b \tag{4}$$

Equation (4) defines a linear combination (z) of input variables (x_1, x_2, ...) weighted by (w_1, w_2, ...) and augmented by a bias term (b). This equation captures the weighted sum, introducing burstiness and perplexity due to the combination of variables and parameters involved. For multiple neurons in a layer:

$$Z - W * X + b \tag{5}$$

Equation (5) represents a linear transformation (Z) of the input vector (X) using weight matrix (W) and bias vector (b). This equation captures the relationship between the inputs and outputs, incorporating both multiplicative and additive components. In the context of a layer with 6 inputs and 3 hidden layers, the equations remain the same. The RE is defined as the ratio of the absolute error between the model prediction and the actual value to the actual value of the observed variable:

$$RE = \left| \frac{\left(predictedvalue - realvalue\right)}{realvalue} \right| \tag{6}$$

The prediction accuracy is calculated using the relative error as:

$$predictionaccuracy(\%) = \left(1 - RE\right) * 100 \tag{7}$$

Equation (6) defines the RE as the absolute difference between the predicted value and the real value, divided by the real value. This equation quantifies the deviation between predicted and real values, providing a measure of accuracy or discrepancy. Equation (7) calculates the prediction accuracy as a percentage by subtracting the RE from 1 and multiplying the result by 100. This equation quantifies the accuracy of the prediction, with a higher value indicating a more accurate prediction.

To build a robust model, the parameters were normalized. The parameters used in the model are discussed below.

4.1 Drop Call Rate (DCR

$$DCR(\%) = \frac{\left(\max\left(A\right) - x\right)}{\left(\max\left(A\right) - \min\left(A\right)\right)} * 100 \tag{8}$$

Where A is the range of the DCR values (excluding the DCR value for the cell with the formula), max (A) is the maximum value of the DCR in the range of values in the table, min (A) is the minimum value of the DCR in the range of values in the table, and x is the current DCR value in the table that is being converted to percentage.

4.2 Power Availability (PA)

The power availability data was grouped into two priority levels according to the industry benchmark at the time of the study.

- if PA ≥ 99.90% (implies PA is Good)
- if PA <99.90% (implies PA is Bad)

Priority levels 1 and 2 have the same expected value for the PA to be considered Good, otherwise Bad.

4.3 CA, CSSR, PTTCH, and HOSR

The CA, CSSR, PTTCH, and HOSR data were grouped into two performance categories. If CA, CSSR, PTTCH, HOSR ≥ 99.0% (implies CA is good, otherwise bad).

4.4 Problem Classification (PC)

We categorized our problem into six categories, each reflecting the problem's nature and being assigned to its corresponding BTS network performance level.

- Problem classification (0) = Excellent BTS network performance level
- Problem classification (1) = Good BTS network performance level
- Problem classification (2) = BTS network not meeting service level agreement.
- Problem classification (3) = Warning
- Problem classification (4) = BTS network is bad
- Problem classification (5) = BTS network is worst

Table 2. *The Binary Classification of the Features*

Performance Levels (PL) of the Features	Binary Classification
PA ≥ 99.9	0
PA < 99.9	1
CA ≥ 99.0	0
CA < 99.0	1
CSSR ≥ 99.0	0
CSSR < 99.0	1
DCR ≤ 0.5	0
DCR > 0.5	1
PTTCH ≥ 99.0	0
PTTCH < 99.0	1
HOSR ≥ 99.0	0
HOSR < 99.0	1

To achieve the manual problem classification, some nested if conditions were met to return the PC values;

For PC {0}

$$If\ PA = 0, \&\ CA = 0, \&\ PTTCH = 0, \&\ DCR = 0, \&\ CSSR = 0, \&\ HOSR = 0, return\ \text{“0”} \tag{9}$$

For PC {1}

$$If\ PA = 0, \&\ PTTCH = 0, \&\ DCR = 0, but\ CA = 1, CSSR = 0, HOSR = 0, return\ \text{“1”} \tag{10}$$

For PC {2}

$$If\ PA = 0, \&\ PTTCH = 0, \&\ DCR = 0, but\ CA = 0, CSSR = 0, HOSR = 1, return\ \text{“2”} \tag{11}$$

For PC {3}

$$If\ PA = 0, \&\ PTTCH = 0, \&\ DCR = 0, but\ CA = 0, CSSR = 1, HOSR \geq 0, return\ \text{“3”} \tag{12}$$

For PC {4}

$$If\ PA = 1, OR\ PTTCH = 1, OR\ DCR = 1, return\ \text{“4”} \tag{13}$$

For PC {5}

$$PA = 1, \&\ CA = 1, \&\ PTTCH = 1, \&\ DCR = 1, \&\ CSSR = 1, \&\ HOSR = 1, return\ \text{“5”} \tag{14}$$

4.5 Binary Classification of Dataset

To facilitate an equitable classification and mitigate the potential for dataset distortion, the quantitative metrics (illustrated in Table 3) were converted into binary representations (as depicted in Table 4). This conversion categorizes the dataset into "acceptable" and "unacceptable" classifications by the mobile telecommunications industry standards pertinent to the locale of this investigation. The "acceptable" category is designated a value of "0", whereas the "unacceptable" category is accorded a value of "1", as detailed in Table 2. A subset of the enhanced dataset is illustrated in Tables 3 and 4.

Table 3. *Gathered data in its raw form*

Raw Dataset From Source Before Normalization						
Index	**PA (%)**	**CA (%)**	**PTTCH (%)**	**DCR (%)**	**CSSR (%)**	**HOSR (%)**
0	100	98.96	99.13	97.92	99.75	98.89
1	100	98.95	99.13	99.55	99.63	98.7
2	100	100	100	99.27	99.8	99.38
3	100	100	100	99.61	`	99.62
4	57.15	52.54	49.65	100	99.79	99.83
.	.	.	.	.	.	.
.	.	.	.	.	.	.
.	.	.	.	.	.	.
861753	100	100	100	99.5	99.86	99.73
861754	100	100	100	99.78	99.85	99.22

Table 4. *Preprocessed data for the DNN model*

Structured Dataset After Normalization						
Index	**PA (%)**	**CA (%)**	**PTTCH (%)**	**DCR (%)**	**CSSR (%)**	**HOSR (%)**
0	0	1	0	0	0	1
1	0	1	0	0	0	1
2	0	0	0	0	0	0
3	0	0	0	0	0	0
4	1	1	1	0	0	0
.	.	.	.	.	.	.
.	.	.	.	.	.	.
.	.	.	.	.	.	.
861753	0	0	0	0	0	0
861754	0	0	0	0	0	0

5. Experiment and Results

The performance of the DNN prediction model for BTS network monitoring and the prediction system was analyzed in various aspects such as data scaling, the bias of the neural network, loss, accuracy, and prediction outcomes of the model. The results obtained from these evaluations are essential to assessing the reliability and effectiveness of the model.

5.1 Bias Analysis

The features were meticulously chosen during the feature engineering phase, concomitantly with the data undergoing comprehensive preprocessing and normalization. This process ensured that the input data was adequately scaled, which is instrumental in facilitating effective learning within the neural network architecture. As depicted in Fig. 2, the bias-over-time graph consistently presents a bias line at the zero mark, signifying that the model remains impervious to over-fitting and is not influenced by outliers. Within the framework of large-scale datasets of this kind and the utilized activation function, bias values customarily oscillate between -1 and 1. The maintenance of zero bias throughout the training process underscores the effectiveness of the data normalization techniques implemented. This result accentuates the enhanced precision and dependability of the model and substantiates its appropriateness for forecasting BTS network failures. The lack of bias further implies that the neurons are suitably balanced, thereby reinforcing the integrity of the deep neural network model.

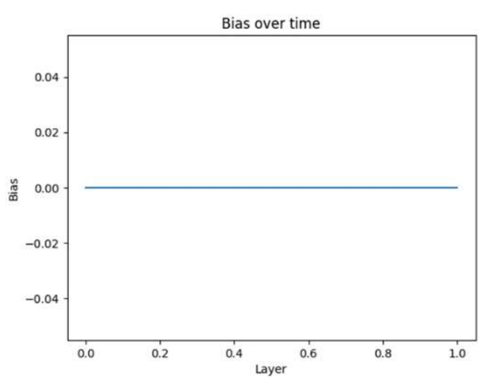

Fig.2. *Plot of Bias over Time*

The DNN model learns and identifies significant data patterns thereby underscoring the capability of neural network-based approaches for addressing challenges in BTS network failure prediction.

5.2 Loss Function

Based on the logical performance classifications, the DNN model quickly finds the pattern and reduces the cost function to zero in very few epochs. Fig. 3 shows the performance of the DNN algorithm in reducing the cost function as the number of iterations increases. The plot reveals a consistent decrease in both training and validation losses as the number of epochs increases. Initially, the training loss and validation loss were relatively high, indicating that the model had not yet acquired sufficient knowledge to make accurate predictions. During this phase, the model was still adjusting its parameters to better align with the training data. Over time, the model steadily improved its performance, resulting in a reduction in both training and validation losses. This observation suggests that the model effectively learned and generalized to unseen data. Furthermore, as the number of epochs increased to 100, the model converged as both the training and validation losses stabilized, indicating that the model operated optimally without over-fitting and variance.

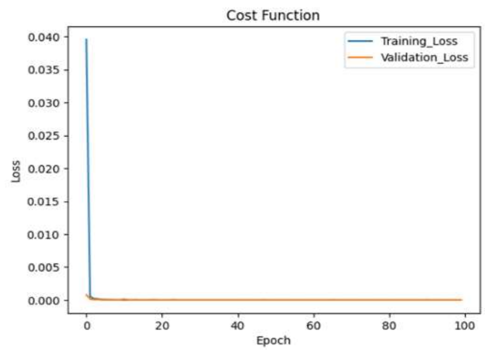

Fig. 3. *Plot of Training Loss vs. Validation Loss function*

5.3 Model Accuracy Evaluation I

Training accuracy denotes the capacity of the model to adequately correspond to the training dataset, whereas validation accuracy evaluates its efficacy on an independent validation dataset. Fig. 3 and 4 demonstrate a consistent augmentation in training accuracy, commencing from a value of zero and reaching a plateau at 99.80% after the seventh epoch, thereby signifying enhanced data fitting. Initially, the validation accuracy exhibits a pronounced increase, progressively aligning with the training accuracy. This alignment at an elevated value implies successful learning characterized by substantial reliability. Notably, the graphical representation indicates that the validation accuracy trajectory remains stable, devoid of any decline, which mitigates apprehensions regarding overfitting.

5.4 Model Accuracy Evaluation II

Fig. 5 illustrates the correlation between actual outcomes and those predicted by the DNN model, which was assessed using a test dataset constituting 10% of the aggregate data. The model successfully predicted 998 out of 1000 outcomes, resulting in merely 2 erroneous predictions. These predictions were evaluated against the actual outcomes derived from the original problem classification framework. The model attained an exemplary prediction accuracy of 99.8%. This accuracy was subsequently corroborated through mathematical validation utilizing equations (6) and (7). In the graphical representation, the diagonal line signifies the region of accurate predictions, whereas the points that lie beyond the diagonal denote instances of missed predictions.

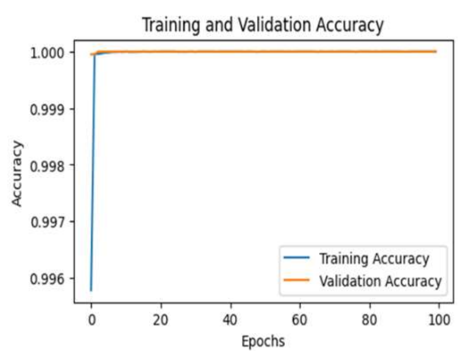

Fig.4. *Plot of Training vs Validation Accuracy*

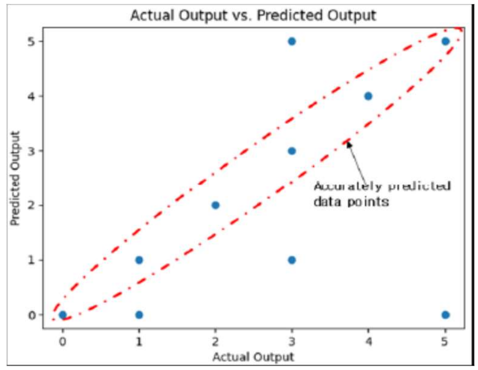

Fig.5. *Plot of Actual Output vs Predicted Output*

5.5 DNN BTS Performance Prediction in Real-Time

The DNN model in this work has been used to classify the entries of the dataset into the six BTS network performance classifications defined earlier. With real-time data, the model, with its high accuracy, efficiently classifies incoming data. With six performance classes, as the output of the DNN goes from Excellent to Not Meeting SLA, network operators are alerted to the drop in performance before it gets further worse. This would reduce the time spent by operators in analyzing network data using traditional means.

6. Advantages of the Proposed Model

Advantages

1. **High Prediction Accuracy:** The proposed model attains an impressive accuracy rate of 99.8%, thereby facilitating accurate predictions of failures in BTS networks and degradation in performance metrics.
2. **Proactive Network Management:** Through the foresight of potential issues before their manifestation, this model empowers operators to implement preventive strategies, thereby enhancing the QoS.
3. **Scalability and Flexibility:** The model possesses the capacity to be modified for various network environments and datasets, ensuring its extensive applicability among telecommunications operators.
4. **Real-Time Monitoring:** It offers instantaneous insights regarding network performance, thereby enabling rapid interventions in response to emergent issues.
5. **Cost and Downtime Reduction:** The implementation of predictive maintenance diminishes the necessity for emergency repairs, resulting in decreased operational expenditures and reduced service interruptions [9].
6. **Optimized Resource Allocation**: The model aids in the identification of inefficiencies within network resources, which contributes to enhanced utilization and overall operational performance.

Disadvantages

1. **Data Quality Dependency:** The efficacy of the model is profoundly contingent upon the acquisition of high-quality, comprehensive datasets. Inaccuracies or deficiencies in the data may significantly impair the precision of predictions.
2. **Complex Data Preprocessing**: The model necessitates considerable endeavors for the cleansing and preparation of data, with inaccuracies during preprocessing potentially influencing the final outcomes adversely.
3. **Risk of Over-fitting:** The phenomenon of over-fitting may transpire, thereby constraining the model's capacity to generalize effectively to novel, previously unencountered data.
4. **Computational Demands:** The implementation of the model necessitates extensive computational resources, which could pose substantial challenges in environments with limited resources.

5. **Integration Complexity:** The incorporation of the model into pre-existing network infrastructures may present complexities, necessitating enhancements to the underlying technological framework.

7. Conclusion

This research developed an innovative DNN model for real-time monitoring and prediction of BTS network performance, employing a comprehensive dataset comprising 861,755 records. Critical performance metrics, which include power availability, DCR, CA, CSSR, PTTCH, and HOSR, were meticulously analyzed. The dataset was systematically partitioned into training (70%), testing (20%), and validation (10%) subsets, with logical frameworks utilized to categorize network performance into six distinct classifications. The developed model attained an exceptional prediction accuracy of 99.80%, surpassing conventional methodologies while furnishing anticipatory insights to alleviate network disruptions ([20][21]). This DNN architecture is designed to integrate effortlessly with pre-existing BTS monitoring frameworks by utilizing hardware components such as edge devices, scalable storage solutions, and GPUs, in conjunction with software tools like machine learning frameworks, APIs, and user dashboards. Such integration facilitates efficient data preprocessing, inference generation, and the derivation of actionable insights, thereby enhancing proactive maintenance, scalability for BTS networks, and economic viability. Consequently, the model is positioned as a resilient and predictive instrument for contemporary telecommunication infrastructures. Furthermore, the inclusion of real-time data streams enhances the system's capability to manage high-density environments, as highlighted by [18].

7.1 Limitations and Future Work

This study faced constraints due to the inability to empirically test the proposed DNN model within an operational BTS network, primarily attributed to privacy and security concerns held by mobile telecommunications operators. Therefore, the model's efficiency in everyday contexts is still to be evaluated.

Future advancements to the model may encompass the incorporation of supplementary network metrics and the examination of the complexities inherent in 5G and 6G networks. Expanding its relevance to 6G technologies may yield vital insights into the management of (URLLC) and address the challenges posed by the anticipated massive device connectivity in forthcoming network generations [17] [6].

Compliance With Ethical Standards

Conflicts of interest: Authors declared that they have no conflict of interest.

Human participants: The conducted research follows ethical standards and the authors ensured that they have not conducted any studies with human participants or animals.

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