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Optimized Neural Network Based Location Prediction Along with Multiple Features in Communication Network

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Abstract:

By the advances in wireless communication networks and the exponential rise in the number of UEs, the data usage is increasing due to time consumption, necessitating lot denser deployment. Extra common handoffs result in superior latency and reduced throughput that have a deleterious impact on network and user acceptance. In this study, we have proposed a ResNet-based Convolutional Neural Network with Tasmanian Devil Optimization (TDO) algorithm for the prediction of location in the communication network. The ResNet-based CNN model with TDO algorithm is used for location prediction, taking into account of wireless quantification findings from service access point and neighbouring core network, and introducing a direction gradient descent to allow the prototype to recognize data on the direction of the UE motion. Comprehensive simulations proved that the proposed model, which is derived from various characteristics and communication flows, performed best result on the prediction of location.

Keywords: Location prediction, Wireless communication, ResNet in CNN and Tasmanian Devil Optimization algorithm.

1. Introduction:

In our daily life, communication networks [1] become an essential part and the growth of communication devices and consumers for universal data access.It is the hardware device that is capable of transmitting or receiving any information. There are multiple types of communication devices [2] they are visual, written, verbal, and non-verbal communications. The information is transferred through graphs, drawings, and photographs. Messages, chats, and emails are used to transfer data. Plenty of references is given for information for written communication devices. Verbal communication [3] is effective in a video conference, presentation, speaking.

Emotions are useful to understand information that is to be conveyed. It is a combined part of hardware and software are the communication systems. The characteristics of data communications [4] are accuracy, delivery, timeliness, and jitter. The various channels [5] are simplex, half-duplex, and full-duplex. In simplex, the data is transferred in one direction. The data is transmitted in both directions is known as half-duplex.In full-duplex mode, the information is transferred simultaneously. The features of communications are a consideration, correctness, clarity, and completeness.

The connected devices direct the signal flow between the transmission modes. In practice, the communication systems are optimized to plan and propagate the information of the users. A neural network [6] consists of input, output, in-between, and hidden layers. The connections are formed by various nodes and nodes are linked with layers. It represents complex computational data and information is stored in the entire network. It directs through only one direction within the layers of nodes. The organizations interact with the system to solve problems and predict to take an accurate decision. Facebook, citations, Twitter is the social media [7] that connect people from different fields.

It can transfer more files through the network. The data rate is high, the cost is low, and signal integrity is possible. Fewer nodes are used, the maintenance cost is high in the development of software and the signal integrity is possible. The file server cost is more requires network manager and it is inaccessible. In this article, we used a novel approach called ResNet-based Convolutional Neural Network with Tasmanian Devil Optimization (TDO) algorithm for the prediction of location in the communication network in accordane with multiple features such as Anchor ratio, iteration, and node density and transmission range

Rest of the article is described as: Section 2 describes the literature works based on the location prediction. Section 3 illustrates the system model and architecture and the proposed methodology is delineated in section 4. Section 5 discusses the experimental results. Finally, the article is concluded in section 6.

2. Literature survey:

Wu et al. [8] proposedamultilayer perceptron (MLP) neural network to predict path loss. The wireless network is optimized by interference and transmitter coverage to analyze the performance. Artificial neural network (ANN), principle component analysis (PCA), and Gaussian process are the combination of path loss. It increases complexity, accuracy, flexibility, and stability. Thus, using path loss prediction models accuracy should be improved.

Lu et al. [9] have developed a joint convolutional residual network (JC-ResNet)to determine the channel state information (CSI) features. The network feedback and quantization channel state information are optimized at a bit level. The quantization deformation is measured by a bit-level optimized design of a neural network. The proposed method is compared to enhance the bit error rate performance and normalized mean squared error. The complexity is higher for large data.

Ramesh et al. [10] have stated an optimized Deep Neural Network algorithm to detect Denial of service in the Wireless Multimedia Sensor Network (WNSMs). To select the features the experiments are determined by unsupervised correlation. The efficiency is tested to evaluate the accuracy and minimum consumption of time.

Different methods such as SVM-DoS, RAS-HO, and TMS are tested to enhance the learning process. Moreover, accurate neural networks can be upgraded.

Goswami et al. [11] have described the Convolutional Neural Network (CNN) for an efficient Industrial Internet of Things (IIoT) network for resource allocation. The resource allocation problems are analyzed to determine the signal interference ratio (SIR). The optimal features are extracted to calculate the channel state information. The network transmits and receives secure data transmission. Compared with previous methods the response time is reduced. Thus, the performance can be achieved by increasing the number of layers.

Shi et al. [12] presented the particle swarm optimization deep neural network (PSO-DNN) algorithm to optimize problems in the number of hidden layer nodes. The network is trained by adding additive white Gaussian noise (AWGN) to determine the performance of the modulated signal. The modulation modes and signals are trained to classify more accurately. This method is faster, more robust, and more effective. Hence, this technique is tested in unknown modulated signals.

Shah et al. [13] propose a field-programmable gate array (FPGA)to compute the coprocessor of a deep convolutional neural network (DCNN). The image is classified by using DCNN. It consists of three layers namely convolution, pooling, and fully connected layers. The extracted input features and the final output is determined for classification. It assists custom precision and data path and enables speed, power, and flexibility. Hence, various techniques are used for better bandwidth.

Ali et al. [14] propose an Optimally Configured and Improved Deep Belief Network (OCI-DBN) based ona stacked genetic algorithm (SGA). It predicts heart diseases and solves overfitting, configuration, and optimization problems. Ruzzo-Tompa is selected to perform the features of an optimal subset. The number of nodes and layers are optimized by SGA and performed in a deep belief network. This method evaluates the precision, Matthew's correlation coefficient, specificity, and accuracy. Thus, the time complexity is investigated.

Illner et al. [15] stated saw tooth inspired pitch estimator (SWIPE) algorithm to determine pitch detectors. The standard deviation and frequencyare estimated to detect the pitch of the proposed method. Pitch Determination Algorithms (PDAs) are examined to test the smartphone devices. To achieve a robust Signal-to-noise ratio (SNR) is combined with algorithms. It is useful to monitor digital biomarkers to evaluate speech therapy. However, pitch changes in smartphones are tracked for sensitivity.

Zhang et al. [16] have described external dimensionality reduction-Factor Analysis (XGBoost-FA). To reduce the dimensional variables information is decreased from factor analysis. The efficiency is increased and the accuracy is improved. From multiple missing data problems of multi-classification is solved.The operating efficiency is improved in every model. Hence, different reduction methods are to be explored.

3. System model and structure:

The historical trajectory UEs are the significant features of mobility prediction. Consider (Y_t, Z_t, T) as the two-dimensional coordinate time series [17]. The latitude and longitudes are represented as Z_t and Y_t. The certain time is denoted as T. Where, $\{L_1, L_2, L_3, L_4,.., L_t\}$ describes the UE trajectory to a time period. The time period length is *t*. At certain time T, the UEs location at few times T is $L_T = (Y_t, Z_t, T)$. The RSRP information is reported by measuring each UE to consider the wireless access network [18]. Where, $p_T = (R_{s,T}, R_{m1,T}, R_{m2,T}, T)$ denotes the neighboring base station. For the prediction of the user's next time location, the measurement reports and the historical trajectory are used. Where, $\{(L_1, p_1),(L_2, p_2),(L_3, p_3),....,(L_t, p_t)\}$ express the combined features [19].

The GPS trajectory data was obtained again from the Geolife project at Microsoft Research Asia [14] to anticipate movement in a complicated environment. There are 17,621 trajectories included in the dataset recorded with one eighty-two customers over a five-year time frame, and each trajectory is symbolized by one sequence of time-stamped points with latitudinal, latitude, and airspeed [20]. Designers select one segment of a

Beijing trajectory dataset. Due to the raw data containing a lot of sounds, and so many positions are focused in a very tiny area, the set of data requires some reprocessing, such as filtration and compacting. The following equation explains the path loss among the base station and UE.

$$Loss(Q)_e = 128.1 + 37.6\log_{10}(e) \quad (1)$$

The distance among the base station and UE is e .

The following equation calculates the RSRP based on the path loss [21].

$$RSRP = R_d - R_{loss} \quad (2)$$

Let us assume the base station of carrier transmit power is R_d that gives 43dBm vales. Table 1 expresses the RSRP values relevant to serving the base station.

Table 1: Information of UE depending upon little time

Name of the data	**Ranges or values**
Y	1634.23m
Z	3725.78m
Longitude	117.324
Latitude	38.99234
Time	08:50:02
Date	23/02/2022
Value of RSRP from next closer base station	-82.62dBm
Value of RSRP from one closer base station	-73.23dBm
Value of RSRP from serving base station	-43.78dBm

The RSRP values and historical location are included in the timeseries to analyze the location prediction. To solve this time-series problem, we introduced an optimized neural network model.

3.1 Problem definition:

From the anchor nodes, the unknown nodes are to estimate their distances using RSSI. Due to multipath fading and shadowing, the power loss is experienced depending upon information exchange [22]. The log-normal shadowing models the path loss and it is denoted as;

$$RL(e) = RL_0 + 10 \times \beta \times \log_{10}\left(\frac{e}{e_0}\right) + Y_f \quad (3)$$

Where, the total path loss of transmitter and receiver power is $RL(e)$ and RL_0 . The distance is *e*. The exponent showing of path loss is β . The log-normal shadowing results experience the ranging error. The below equation expresses the value of variances ϑ

$$\vartheta^2 = \alpha^2 \times E_{jk}^2 \quad (4)$$

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The localization error among the measured Euclidian distance E_{jk} and actual distance is α . Equation (5) computes the real distance E_{jk} .

$$E_{ij} = \sqrt{(y_j - y_k)^2 + (z_j - z_k)^2} \quad (5)$$

Equation (6) represents the measures distance $E^{`}_{jk}$.

$$E^{`}_{jk} = E_{ij} + M_{jk} \quad (6)$$

The ranging among nodes j and k is M_{jk} . The mean square error among the estimated actual unknown node coordinates and actual distance of evaluated node coordinates are formulated via optimization function (*ofn*) [23].

$$ofn(y_j, z_j) = \frac{1}{N} \times \sum_{k=1}^{N} (E_{jk} - E^{`}_{jk})^2 \quad (7)$$

The j^{th} position of unknown node positions is (y_j, z_j) and (y_z, z_z). Evaluate the unknown node position is minimum value of optimization function.

4. Proposed Methodology:

In this study, we proposed a ResNet-based CNN approach with respect to the Tasmanian Devil Optimization (TDO) algorithm for the purpose of predicting locations in the communication network.

4.1 Importance of features:

The ResNet-based CNN approach evaluates the importance of features. The importance predictors are plotted in Figure 1. The node density is the most important of the four features, abided mostly by epochs. The anchor ratio, on the other hand, is nearly as important as the transmission range [24]. Furthermore, we calculated the features' incomplete dependence on the prediction. Users as well obtained by plotting the personal conditional probability from each data point in the same plot.

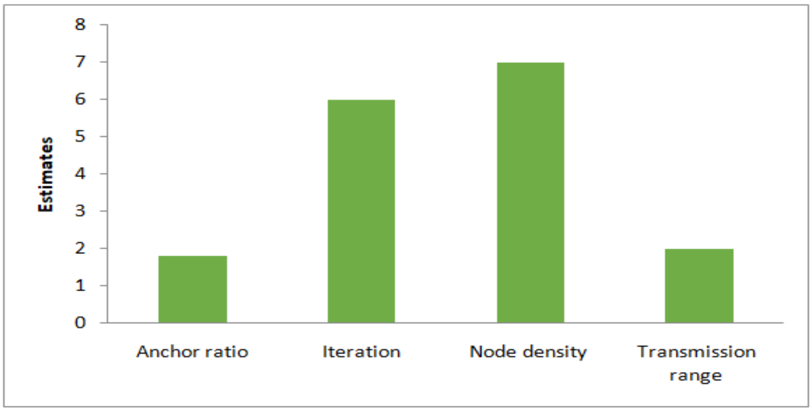

Figure 1: Plots for importance predictors

4.2 ResNet-based CNN model:

The ResNet-based CNN approach divides the neural network into smaller chunks, which are referred to as Lingering Blocks [25]. This method can be used to deepen the neural network while also removing Disappearing Conjugate gradient issues that also reduce achievement effectiveness as the neural network becomes wider. The residue left blocks are linked inside winds up and packet regularisation activities are performed [26]. The ResNet is used to regularise the mean and variance in neural network models. This is referred to as a drop-out impact. The architecture of ResNet model is depicted in Figure 2.

The diagram depicts the configured ResNet CNN, which has seven basic block layers upon layer. Two residual blocks are stored in each layer. Ordinarily, this same DA result is conveyed to a permutation feature, and then average pooling and function activation are performed. The ReLU feature appends the input to the output and transmits it. It is carried out in the ResNet Sheet module [27]. The human brains transfer the information images to the ResNet layer, resulting in the predicted output. The layer's depth involves internal characteristics of the distribution.

The error back-propagation algorithm method is used in the proposed approach to conquering the error inside the expected values. The above technique is based on the adaptation of every node weight to reduce the incidence of faults for each node. It proceeds back into the past, from the output node to the corresponding input source [28]. Furthermore, it is unavoidable to select the precise optimization method in order to minimize the gap amongst some of the nodes. Utilizing neural network-based improvement, the error here between input data is approximated as a gradient. As a result, the node with the fewest errors is chosen for the next step, lowering the likelihood of a fault occurring.

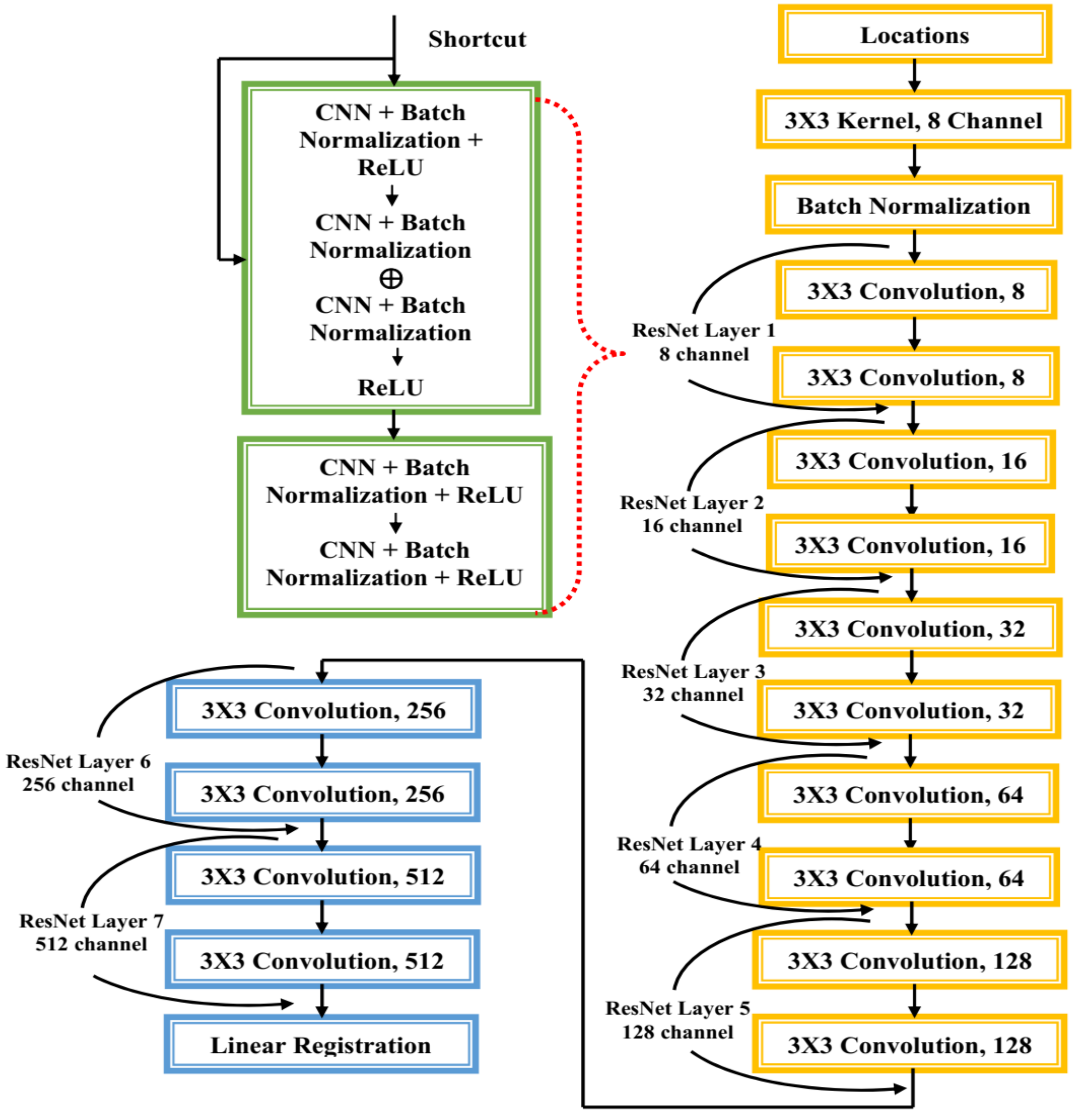

Figure 2: Architecture of ResNet model

The location prediction takes the baseline data shape into account as much as the other strategies. The Adam GD, RMSProp, AdaGrad and SGD can accomplish this. Based on SGD, the slope error rate $\frac{\partial g}{\partial W}$ is used to represent the gradient descent of the weighted parameter *W*.

$$W \leftarrow W - \varphi \frac{\partial g}{\partial W} \tag{8}$$

This same slope is defined also as an increase in the prices of *g* throughout relation to the value of W. The individual's learning rate is determined as φ. In the meantime, according to the AdaGrad, the error rate of the graded variable *W* is affected by the *f* worth, that also represents the varying information gain [29]. Then it can be stated as,

$$W \leftarrow W - \varphi \frac{1}{\sqrt{f}} \times \frac{\partial g}{\partial W} \tag{9}$$

The following equation can be used to reduce the value of *g* in this case.

$$f \leftarrow f + \frac{\partial g}{\partial W} \cdot \frac{\partial g}{\partial W} \tag{10}$$

This method works well for detecting simple shaped objects but performs poorly for detecting intricate shapes. RMSProp was used to create this shape. The technique can be stated as follows:

$$f_i \leftarrow \varphi f_{i-1} + (1-\varphi) \frac{\partial g_i}{\partial W} \cdot \frac{\partial g_i}{\partial W} \tag{11}$$

4.3 Tasmanian Devil Optimization (TDO) algorithm:

The TDO is based on the carnivorous animal Tasmanian devil from the family of Marsupial wild animal [30]. The algorithm is based on the eating strategy of the animal (i) feeds carrion, and (ii) hunts and feeds the prey by assaulting it.

(i) Initialization:

The population is initialized based on the location prediction in the search space. Moreover, the population is randomly generated and relies on the boundary levels of the issues. The member set can be initialized as shown below,

$$M = \begin{bmatrix} M_1 \\ \vdots \\ M_j \\ \vdots \\ M_X \end{bmatrix}_{X \times Y} = m \begin{bmatrix} m_{1,1} & \cdots & m_{1,k} & \cdots & m_{1,y} \\ \vdots & \ddots & \vdots & \iddots & \vdots \\ m_{1,1} & \cdots & m_{j,k} & \cdots & m_{j,y} \\ \vdots & \iddots & \vdots & \ddots & \vdots \\ y_{X,1} & \cdots & m_{X,k} & \cdots & m_{X,y} \end{bmatrix}_{X \times Y} \tag{12}$$

The jth candidate of the Tasmanian devil population is M_j. The kth candidate variable can be indicated as $m_{j,k}$. The objective function can be evaluated from all the possible candidate solutions [31]. It can be described as,

$$H = \begin{bmatrix} H_1 \\ \vdots \\ H_j \\ \vdots \\ H_X \end{bmatrix}_{X\times 1} = \begin{bmatrix} H(M_1) \\ \vdots \\ H(M_J) \\ \vdots \\ H(M_X) \end{bmatrix}_{X\times 1} \tag{13}$$

H denotes the vector of objective function and the jth candidate solution is illustrated as H_j.

(ii) Exploration stage:

It relies on the carrion selection from the ith member of the population. The arbitrary selection of the carrion can be performed by the following conditions.

$$CO_j = M_i, \quad j = 1,2,..., X, \quad i \in \{1,2,...., X | i \neq j\} \tag{14}$$

CO_j denotes the j^{th}Tasmanian devil incorporated with the selected carrion. Estimation of new carrion from the search space of the Tasmanian devil is performed and updates the new search agent as expressed below,

$$m_{j,k}^{new,A_1} = \begin{cases} m_{j,k} + b\cdot\left(d_{j,k} - I\cdot m_{j,k}\right), & Hd_j < H_j \\ m_{j,k} + b\cdot\left(d_{j,k} - m_{j,k}\right), & else \end{cases} \tag{15}$$

$$M_j = \begin{cases} M_j^{new\cdot A_1}, & H_j^{new\cdot A_1} < H_j \\ M_j, & else \end{cases} \tag{16}$$

The new status of the jth devil is illustrated as $m_{j,k}^{new,A_1}$. The random number b falls under the interval of 0 and 1 with the objective function $H_j^{new\cdot A_1}$. It is also a random number and lies between 1 and 2.

(iii) Exploitation stage:

The location of prey can be assumed by the Tasmanian devil depending on the population. The location of the prey can be formulated as shown below,

$$L_j = M_i, \quad j = 1,2,..., X, \quad i \in \{1,2,...., X | i \neq j\} \tag{17}$$

The location of selected prey with the jth Tasmanian devil is indicated as L_j. after the improvement of the target function the estimation of the location of the Tasmanian devil is,

$$m_{j,k}^{new,A_2} = \begin{cases} m_{j,k} + b\cdot\left(q_{j,k} - I\cdot m_{j,k}\right), & Hq_j < H_j \\ m_{j,k} + b\cdot\left(m_{j,k} - q_{j,k}\right), & else \end{cases} \tag{18}$$

$$M_j = \begin{cases} M_j^{new\cdot A_2}, & H_j^{new\cdot A_2} < H_j \\ M_j, & else \end{cases} \tag{19}$$

The new location of the jth Tasmanian devil is $m_{j,k}^{new,A_2}$ and its respective objective function is Hq_j. The new location can be predicted by the estimation of a greater value from the objective function. The updated procedure of the Tasmanian devil is estimated as,

$$B = 0.01\left(1 - \frac{1}{T_{\max}}\right) \tag{20}$$

$$m_{j,k}^{new} = m_{j,k} + (2b-1)\cdot B \cdot m_{j,k} \tag{21}$$

$$M_j = \begin{cases} M_j^{new\cdot}, & H_j^{new} < H_j \\ M_j, & else \end{cases} \tag{22}$$

Here, t and $T_{\max}$ denotes the ongoing and maximum number of iterations.

The current and maximum number of iterations is $t$and $T_{\max}$. Thej^{th}Tasmanian devil neighborhood of Y_j with its new status is $Y_j^{new\cdot}$. The objective function value is H_j.The flowchart representation of the TDO algorithm is delineated in Figure 3.

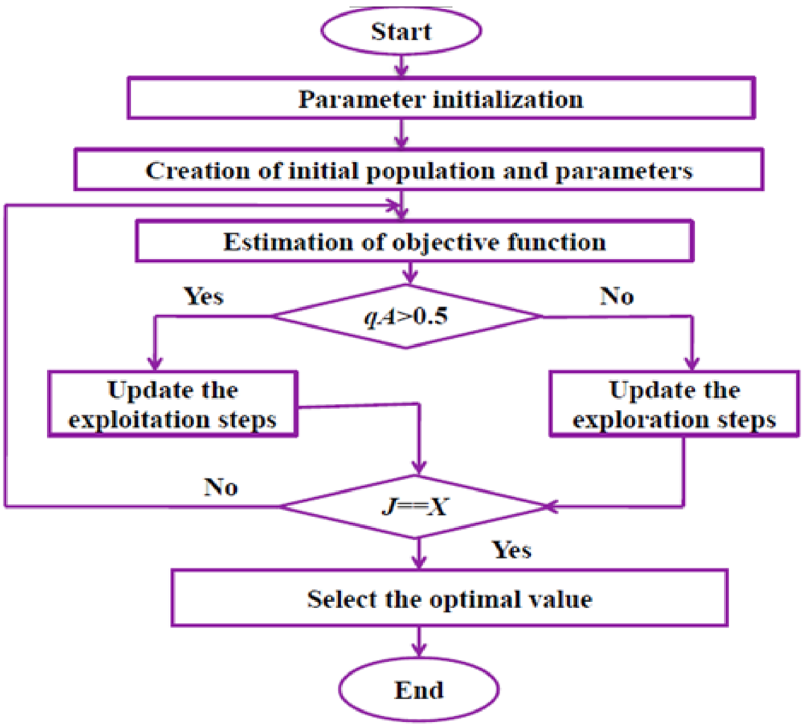

Figure 3: TDO algorithm flowchart

4.4 Proposed ResNet based CNN with TDO algorithm for location prediction:

The node localization in WSNs is performed via proposed ResNet-based CNN with TDO algorithm. The performance of ResNet based CNN model is boosted via TDO algorithm, which has higher convergence performance with lesser complexity. This model estimates the exact location of the show's nodes by selecting a random optimization algorithm for each node [32]. Following that, it computes the global optimum for every remedy to use the optimization function described in equation (7). A new set of random assignment possible solutions replaces one of the worst feasible solutions. The above procedure is iterated for predefined iterations, after which the locations correlating to the worldwide optimal solution are chosen as the exact location of the show's nodes for every base station [33].

The hyperparameters in the ResNet model such as the number of layers and activation functions are optimized via the TDO algorithm. During optimization, the objective or loss function as the mean square error is measured as follows;

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$$\frac{1}{m}\sum_{j=1}^{m}\left(Z_j - \hat{Z}_j\right)^2 \qquad (23)$$

The four features such as a number of iterations, node density, and transmission range and anchor ratio are extracted with the help of proposed ResNet-based CNN with TDO algorithm.

5 Experimental Investigations:

The location prediction can be performed by setting 10 points in a sequence that includes Reference signal received power and geographic coordinates based on the base station and its respective adjacent stations [34]. The total number of sequences after performing the proposed method is 20010 [35]. These sequences are separated into two parts training and validation data. The parameter settings are listed in table 2.

Table 2: Parameter settings

Parameter	Range
Learning rate	0.001
Iterations	150
Batch size	127
Reduction of learning rate	0.1
Optimizer	Adam

The graphical representation of the training dataset out of total value is depicted in figure 4. The accuracy of the training dataset almost lies between the range 0.996 to 0.999. And the validation dataset result is illustrated in figure 5. The accuracy of the validation set lies between the range of 0.98 to 1.03.

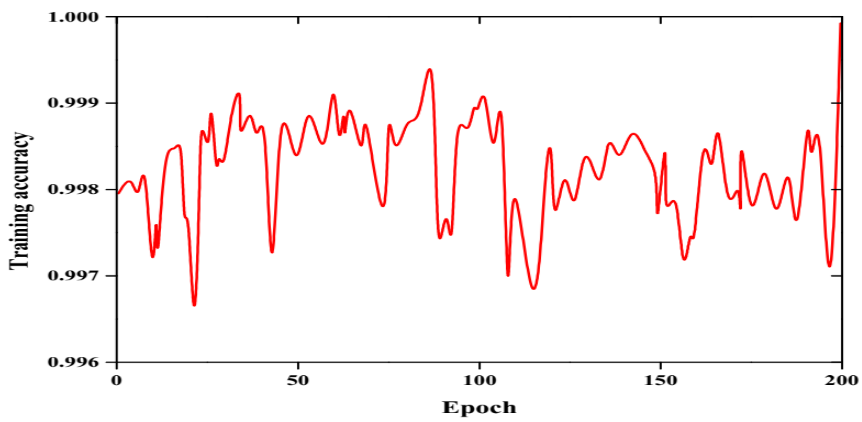

Figure 4: A plot of the training set's accuracy calculation

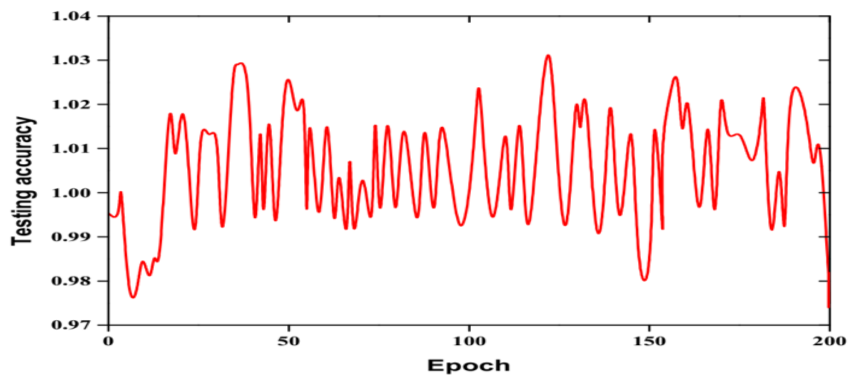

Figure 5: A plot of the validation set's accuracy calculation

The performances of the proposed method are analyzed by considering the input features and comparing the results with the geometric coordinate without the inclusion of cosine proximity loss. Moreover, we also analyzed the Euclidean distance error among the actual location and predicted location. Besides, the accuracy of the connectivity of the UE is based on the base station.

Table 3: Estimation of distance error with various Features

Features	**Position**	**Position+RSRPs**	**Position+RSRP$_N$+RSRPs**	**Position+2RSRP$_N$+RSRPs**
CNN	49.367	43.478	39.409	38.217
Resnet in CNN-TDO	43.765	38.901	37.278	37.024

The distance error for various features is illustrated in table 3. It shows the distance error when the data is trained with CNN and ResNet inCNN-TDO approaches. From table 2 the distance error is low for the multiple features such as position, 2RSRP$_N$, and RSRPs which is 37.024. the distance error is high when the feature selection is the only position that is 49.367. the location prediction distance error based on different features is illustrated in figure 6. From the figure, we can calculate the distance error in meter is less when we use more features for the prediction of location using our proposed method.

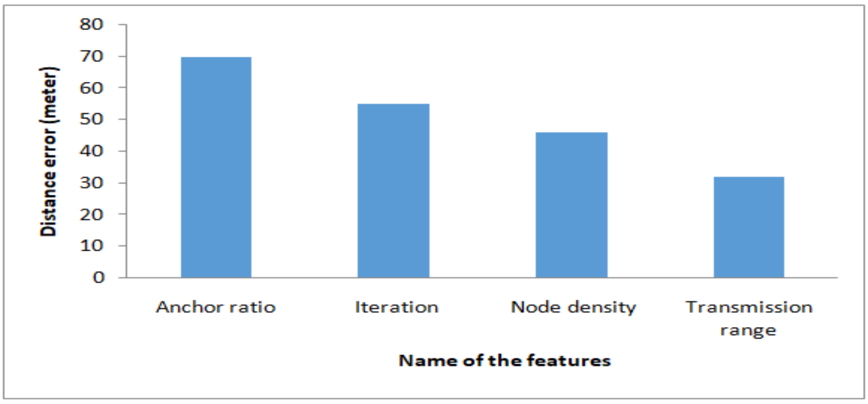

Figure 6: Distance error prediction using different features over our proposed method

5.1 A comparative study based on the Performance measures:

For comparative study, we have taken the metrics such as accuracy, precision, recall, sensitivity, F1-measure.

Accuracy:

It is defined as accurately predicting the location using geometric points and sequences. This relies on the total recognized values, and the ratio of the correctly recognized value is defined as accuracy. It can be expressed as,

$$Accuracy = \frac{\sum_{x=1}^{t}(TP_x + TN_x)}{\sum_{x=1}^{t}(TP_x + TN_x + FP_x + FN_x)} \tag{24}$$

Based on the above equation, FP_x, FN_x, TP_x and TN_x represents the false positives, false negatives, true positives, and true negatives.

Precision:

According to the total predicted location, the closest values or positively predicted location estimation is determined as precision. It can be expressed as,

$$Precision = \frac{\sum_{x=1}^{t} (TP_x)}{\sum_{x=1}^{t} (TP_x + FP_x)} \quad (25)$$

Recall:

The recall is a calculation that indicates how many correct positive locations were predicted out of all potentially predicted values.

$$Recall = \frac{\sum_{x=1}^{t} (TP_x)}{\sum_{x=1}^{t} (TP_x + FN_x)} \quad (26)$$

Sensitivity:

From the false negative and true positive identifications, the accurate prediction of positives is defined as sensitivity.

$$Sensitivity = \frac{\sum_{x=1}^{t} TP_x}{\sum_{x=1}^{t} (TP_x + FN_x)} \quad (27)$$

F1 score:

The accuracy of the test dataset measures the F1-score. Both precision and recall calculate the f1 score and it lies between [0, 1].

$$F1 - score = \frac{2(Precision \times Recall)}{Precision + Recall} \quad (28)$$

To analyze the performance and to make the comprehensive comparative study we have taken some state-of-art works known as WNSMs, PSO-DNN, and OCI-DBN- SGA. Figure 7 delineates the accuracy of the location prediction by our proposed and other methods. From the figure we investigated that the proposed approach effectively predicts the location more than the other approaches. The inclusion of TDO improves the prediction accuracy, more than that it also enhances the convergence speed and thus our approach predicts the location using the features we deemed earlier. The prediction accuracy of our proposed approach is 98.45%, wherein the approaches WNSMs, PSO-DNN, and OCI-DBN- SGA obtain the accuracy of 79%, 89%, and 94.67% respectively.

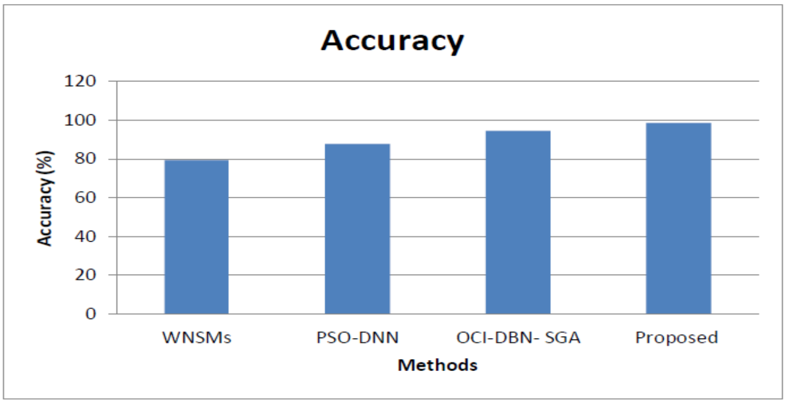

Figure 7: Accuracy based Comparative study

Figure 8 illustrates the precision of the proposed approach and its comparative study. The precision of our proposed approach is 97.58%, and other approaches WNSMs, PSO-DNN, and OCI-DBN- SGA achieve 89%, 86.49%, and 93.07% correspondingly.

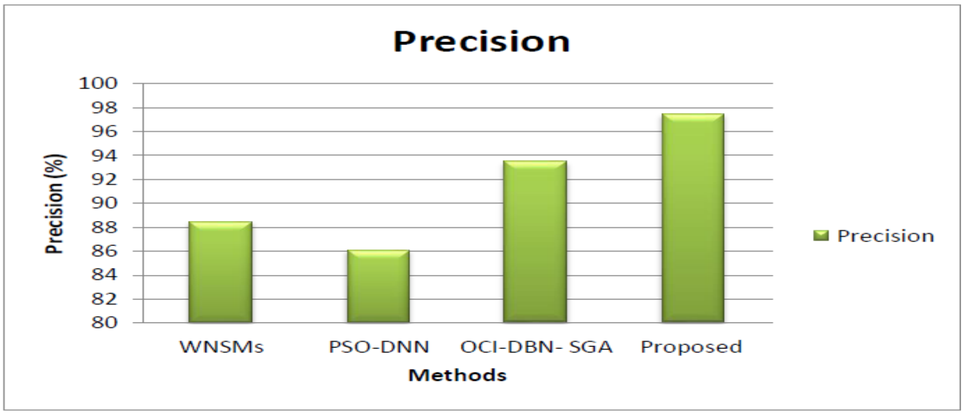

Figure 8: Precision based Comparative study

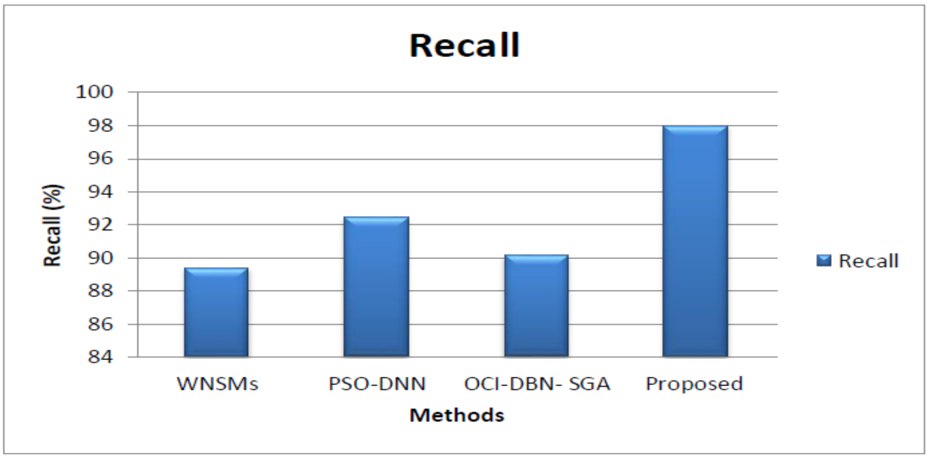

Figure 9: Recall based comparative study

The recall-based comparative study is deliberately explained in the graphical curve depicted in figure 9. From the figure, we can notice that the proposed approach exhibit higher recall with the inclusion of the ANN with the TDO. The sensitivity-based comparative study is elucidated in figure 10. The method OCI-DBN-SGA achieves the least sensitivity of 88.67% and our proposed approach exhibit higher sensitivity of 97.56%.

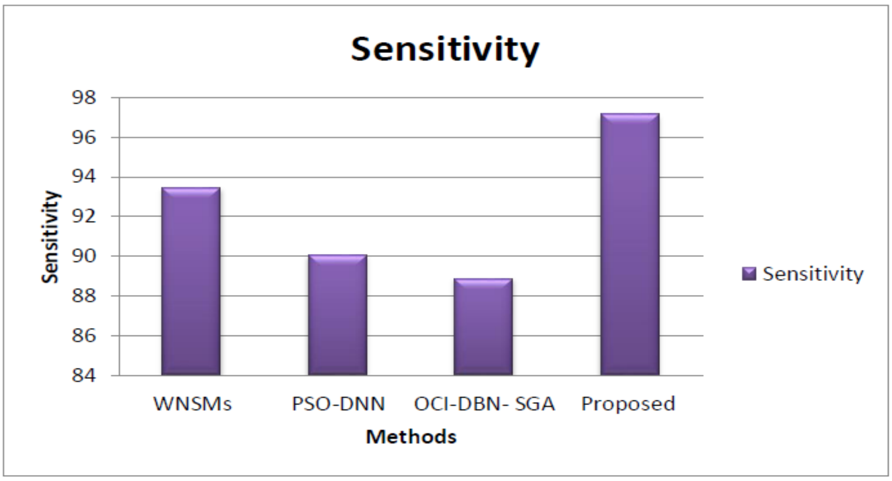

Figure 10: Sensitivity based comparative study

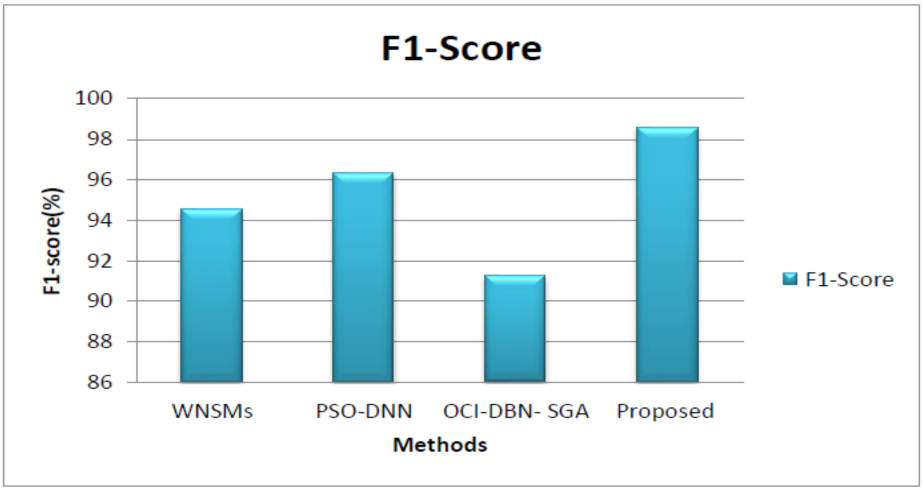

Figure 11: F1-Score based comparative study

Figure 11 illustrates the F1-score-based comparative analysis and from the graphical representation, we can investigate that the proposed approach achieved a better F1-score of 98.76% and the OCI-DBN-SGA exhibited the least percentage of 91.74%.

6 Conclusion:

This article presented a ResNet based Convolutional Neural Network with Tasmanian Devil Optimization (TDO) algorithm for the prediction of location in communication network.Instead of simply to use the UE's historical trajectory, the proposed model based position forecasting on multiple features. The proposed model uses wireless quantification findings from of the allowed to serve base station and neighbouring base stations to anticipate the UE's upcoming position by combining the UE's chronological position including its correlating RSRP values. We initiate the gradient descent, that is constituted of the range team losing and the direction lost opportunity, to allow the proposed model to learn information on the UE motion path. Multiple features, like path and wireless quantification RSRP, offer extra details again for location forecasting model in the communication system, assisting in wireless optimization and vehicular networks.

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