LOL-SM-Lion Optimization adapted Spectrum Distribution for Cognitive Radio Enabled Vehicular Ad-Hoc Network

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Abstract: The Vehicular Ad-hoc Network (VANET) is massively used in challenging traffic regulatory systems in the recent times. The bulky data being articulated by VANET is the critical part leading to the spectrum limitation issues. Cognitive Radio (CR) technology is a prominent stream to manage uncertainty in the spectrum distribution. The CR chooses the idle path in the entire spectrum and allocate as per the requirement for handling smooth traffic flow. Furthermore, parameters such as a multipath fading, primary user static problem and dynamic topology of vehicular communications remains to be challenge for implementing the CR in VANET for an effective and intelligent spectrum distribution. Moreover conventional methods for CR-VANET spectrum allocation is limited yet to handle Considering the higher mobility and uncertainty constraints, a novel deep learning adopted CR-VANET model is proposed. This paper proposes the new deep learning model which works on the principle of Lion Optimized Long Short Term Memory (LOL-SM) models which overcomes the drawbacks of the traditional LSTM and these learning models are implemented in the road side units (RSU) which predicts the vacant models and sends it to the vehicles. Comparing with the existing spectrum sensing strategies, the proposed LOL-SM based -CR VANET model attains a reduced overall transmission delay with minimum loss probability. Also, the false alarm rate is almost nullified in the proposed approach thus enhancing an effective spectrum usage in VANETs

Keywords: VANET, Cognitive Radio Networks, Lion Optimization, Deep Learning, Traffic management

1. Introduction

SECTION-I

Vehicle on-road tracking is an important constraints in maintaining a smooth traffic flow. In metropolitan cities, the tremendous usage of vehicular transportation is a challenging part in traffic flow management. Despite of the advancements in road safety and traffic flow managements, the accident rates are still alarming. In order to limit such cases, the upcoming technologies should cope with proper safety measures. The vehicle to vehicle communication is the important requirement to avoid congestion and accidents. Also a control unit for monitoring the overall traffic flow should be a regulatory system to control the vehicles based on their mobility rates. Construction of a prominent Vehicular Ad-hoc Network can adhere with all these requirements. VANET comprises of Intelligent Transportation and wireless communication with the surrounding environments [1-3]. The advancements in wireless devices helps in transmission of high- volume data. The current demand in wireless networks are spectrum requirement to allot and transmit the vast data. Owing to the tremendous data usage of around 4 terabytes after the advancements in wireless networks, access to cloud based on Internet of Things (IoT) is mostly preferred. As the population of vehicle increases, the data collision can occur. Here, the proper allocation of bandwidth is the vital requirement for an efficient VANET. The dynamic spectrum accessing (DSA) mechanisms are great boon to spectrum limitation problems. DSA models such as CR can handle the spectrum allocation efficiently. These networks chooses the idle or unused spectrum termed as spectrum holes and utilize them as secondary channels. Thus binding the CR with VANET model will act as an efficient traffic management system which is shown in Figure 1.However, an intelligent idle spectral path selection is the need for the day. The proper channel state selection reduces the congestion, false alarms and packet misplacement.

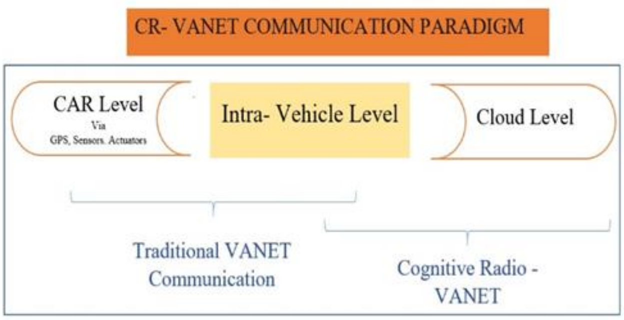

Fig 1. CR-Vanet Communication Flow Diagram

The state decision is thus prioritized in a VANET model to manage the intense mobility. Deep learning approaches can be helpful to intelligently decide the channel and packet allocation for an efficient spectrum sensing in CR-VANETs. The performance of the VANETs can be improved by optimizing the parameters to attain desirable solutions. In the existing VANET designs, the reinforcement based DL architectures are employed to handle spectrum allocations. Achieving optimized solution for decision making of link establishment is still challenging in heavy traffic flow. To overcome such optimization issues, the proposed model aids in faster updation of channel state condition to develop an efficient VANET model. The contribution of the work is as follows as

1. The development of novel deep learning model based on Lion Optimized LSTM algorithms for an effective prediction of the vacant spectrum spaces as sent to the vehicles.

2. The adoption of hybrid adaptive spectrum sensing to overcome the multi-path fading due to the dynamic mobility in the vehicular communication.

The organization of the paper is as follows as Section -II presents the various related works by more than one authors. Section-III discusses about the preliminary views of Long Short term memory (LSTM) and Lion Optimization techniques. Section-IV discusses about the System model and working mechanism of the proposed algorithm has been presented in Section-V. The experimental setup, result analysis along with the different comparison is presented in Section-V. Finally, the section-VI discusses about the conclusion and future scope.

SECTION -II

1. Related Works

In the recent years, several conventional studies have been conducted so far to develop an efficient traffic management system. Joy et al [4] introduced a model to observe and detect freely wandering spectrum holes in the network. This initiation is effective to choose the unused spectrums. Farwaz et al. [5] proposed an idea to increase the bandwidth of the spectrum being assigned. This allocates the free spectrum with a wireless access in vehicular environment (WAVE) model. Though the model supports spectrum distribution, still the necessity for spectrum is vast. Shah et al. [6] developed a model to incorporate CR network with VANET. The model also attempted to access the free spectrum using WAVE network. The demand for transmission speed is the setback since it is non-compensatory. Abeywardana et al. [7] proposed a model to incorporate the CR with VANET using conventional FIFO basis. The urgency label is neglected which is not appreciable in emergency conditions. Chung et al [8] proposed a MAC network based VANET model. This completely depends on the spectral allocation as per demand. Additional spectrum are always conserved and kept ready to use on demand. Li et al [9] developed a belief propagation model (BPM) to efficiently distribute the spectrum to the entire window. According to them, each vehicle has to develop their own belief based on their requirements. The beliefs are labels for spectrum assignment. Wang et al. [10] proposed an efficient CR-VANET model. Hung et al. [12] introduced a model to detect the idle spectrum for transmitting safety messages in VANET. This model gains a higher packet reception rate and reduced delay than other conventional models. This solved the major uncertainty issues in rural traffic scenarios. Yet intelligent channel selection is expected in high mobility conditions. Muraleedharan et al. [11] introduced swarm intelligence based CR-VANET. This put forth an idea of developing some intelligent learning strategies to achieve optimum management.

The machine learning algorithms used so far in the literature is intended to ease the network performance of CR-VANET. The performance of the network includes less delay, reliable route selection, secure link establishment and energy efficiency. The ML methods can help in proper scheduling of channel states and to line up the messages based on their importance.

Liang et al. [13] proposed a machine learning ideology to intelligently deicide and optimize paths for spectrum allocation in vehicular network. Particularly, the model is trained with reinforcement learning to eliminate optimization steps. Atul B.Kathole et al. [14] proposed a ML classifier for VANET model. The intrusion detection classifier helps in identification of troops in the spectral bands. The sensitive nodes are constantly monitored by the learning algorithm. Xin Lin Haug et al. [15] developed a prediction model to locate the best path to improve the performance. This is based on Bayesian model based on supervised learning for the detection of correlation of data points using data mining algorithm. Christopher Chembe et al. [16] developed a VANET model based on reinforcement learning approach. This locates the spectrum PU and predict the channel to be free in near future. The road side unit (RSU) is implemented with the learning steps for avoiding shadow and fading effects. Hyung Ju Cho et al. [17] proposed a continuous range K- nearest neighbor queries in VANETS. The clustering idea of KNN aids in allocation of packets and model the links in the network.

In order to overcome these limitations, the proposed system includes an intelligent deep learning based approach with lion optimization for efficient spectrum selection. The uncertainty issues are minimized with the proposed LOSD CR-VANET Model. The data sensed from the vehicles are clustered using deep learning algorithm with lion optimization to intelligently use CR for proper spectrum allocations.

SECTION -III

3.1 Prelimiinary Overview

1. LSTM Network

LSTM Network is the variant of Recurrent Neural Network (RNN), which can enhance the learning based on sequential prediction strategies. Usually in RNN architecture, the inputs are not a fixed feature rather, the input comprises of a sequence of data which has to be conveyed as a sequential output after performing the expected function. As the model works on sequential data, the output depends on previous data values. Hence RNN uses gates as memory cell to store data. Each memory cell in the model gets connected to the hidden layer neuron and their respective gate fields. The basic structure of LSTM is shown in Fig 2.The major concept of LSTM is based on short term dependency. The three gates in the network includes a Forget Gate, Input Gate and Output Gate. The dependency criteria in the LSTM model prone way to vanishing gradient problem in RNN. This is because of the convergence issues because of consecutive state changes. So optimizer is appreciable in LSTM models to achieve better accuracy.

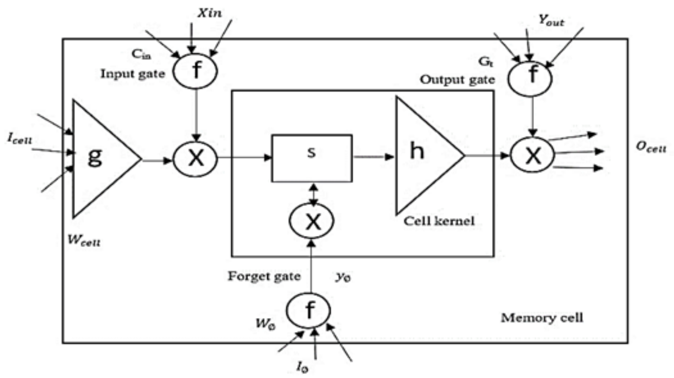

Fig 2. LSTM Network -Overview

2. Lion Optimization

Bio-inspired optimization algorithms are developed from the inspiration of the natural living behavior of a group of living beings. Based on the social-behavioral features of lion. Raj Kumar et al [16] came up with an idea of adopting the unique behaviors of Lion, the strongest mammal. The Lion's social behavior is that a male and female lion starts to live together as Pride in a territorial space. The Cub born to them will be with the male and female lion for two to four years. Between some nomadic lions try to invade the territorial place. The male lion have to protect the territorial space by defending the nomadic lion. If the nomadic lion defeats the territorial lion, it kill the lion and its cubs forming a new pride.

Thus, the Lion inspired algorithm is adopted to achieve optimization in four different means. The initial stage is Pride Formation which generates random solutions. The second stage is Matting which refers to locating new solutions. The third stage is the territorial defense based on clustering process. The final stage is territorial takeover which defends the laggard solution finding the one best solution.

The Lion Optimization is initialized by randomly choosing a solution space *Z*. Each solution is termed as

$$Cluster = \{a_1, a_2, a_3 \dots a_N\} \qquad (1)$$

Where *N* is the dimension of the solution space *Z.* The fitness function of the cluster is expressed as

$$Cost\ of\ cluster = f(Cluster) = f(a_1, a_2, a_3 \dots a_N) \qquad (2)$$

The success of the resident male lion by setting its own pride can be

$$L(i,t,P) = \begin{Bmatrix} 1\ ,best\ male\ if\ t < t-1 \\ 0, for\ else\ other \end{Bmatrix} \qquad (3)$$

The Nomad Lions roam randomly to occupy the pride space *Z*. This trapping can be executed as

$$Cluster_{i,j} = \begin{Bmatrix} Cluster_{i,j} if\ Rand_j > P_n \\ Rand_j, Otherwise \end{Bmatrix} \quad (4)$$

where $Rand_i$ is the randomly generated new vector space. P_n is the Probability of Nomad succession which is defined as

$$P_n = o.1 + \min\left(0.5, \frac{Nomad - Primitive\ Nomad}{Primitive\ Nomad}\right) \quad (5)$$

Thus the primitive nomad will be the successor of the pride space *Z.*

System model:

Primary user activity modelling

The transmission phase of the PU transmitter directly relates the performance tolerance of the entire spectrum sensing model. The perceived VANET model can hold either in ON state or OFF state. The probability of PU being at ON state be

$$\rho ON = \frac{\alpha}{\alpha+\beta} \quad (6)$$

and

$$\rho OFF = \frac{\beta}{\alpha+\beta} \quad (7)$$

where α and β corresponds to the ON and OFF state respectively.

For the probability of PU remaining ON for the sensing window period as an exponential distribution function is

$$P_{ON} = \rho ON . exp\left(-\frac{M}{\alpha}\right) \quad (8)$$

and the probability of PU remaining in OFF state for the sensing window period as an exponential distribution function is

$$P_{OFF} = \rho OFF . exp\left(-\frac{M}{\beta}\right) \quad (9)$$

The transition states of switching of PU from ON and OFF be calculated as the probability of transition as

$$P_T = 1 - P_{ON} - P_{OFF} = 1 - (P_{ON} + P_{OFF}) \quad (10)$$

$$P_T = 1 - \left[\frac{\alpha}{\alpha+\beta} . exp\left(-\frac{M}{\alpha}\right) + \frac{\beta}{\alpha+\beta} . exp\left(-\frac{M}{\beta}\right)\right] \quad (11)$$

To regulate this transition states, the proposed model has effectively predicts the PU with a proper transition cycle

SECTION-IV

4.1 Proposed Sensing Technique Using LOL-SD algorithm:

4.1.2 System Overview:

Many sensing methods such as double tier co-operative sensing using different features has been used for vehicular communication. But still, these algorithms fails in identifying the primary users correctly du to the dynamic mobility environment of the vehicular networks. Hence this research work proposes the new deep learning models which provides the superior performance in the dynamic mobility environment. The proposed deep learning based spectrum sensing technique is purely depends on the energy vectors which are then used to train the model. The Lion optimized LSTM network has been proposed for an effective prediction and sensing of the spectrum. These algorithms are implemented in road side unit of vehicular communication (RSU).

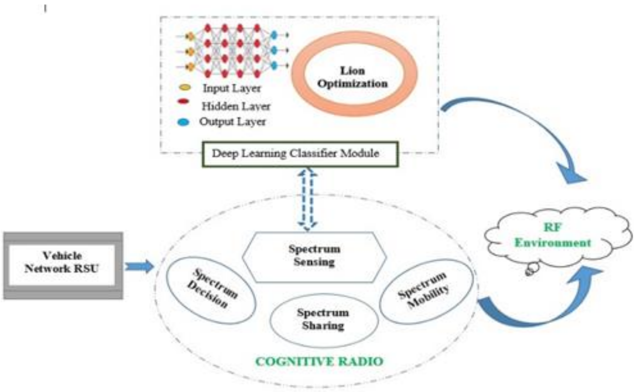

Fig .3 Proposed LOL-SD CR VANET Architecture

4.1.2 Feature Extraction:

The stages in RSU processing comprises of two stages. Initially the density of the vehicles are estimated and in the second stage, the PU channel selection based on the availability of free channels in the RF environment. The on road vehicles have to sense the free spectrum holes in the chosen licensed channel. Further the network will take decision regarding the transmission of packets when the channel is free. The two antennas in the vehicle helps in administrating communication to the DSRC and to estimate the unoccupied PU channels. The on road segmentation involves the splitting up of the entire RSU into regions. Some extra spectrum should be reserved for congestion avoidance.

The VANET model considers each frame as T and the sensing time instance beT_s. The time taken for one complete transmission phase be $-T_s$. The flow diagram of the process is shown below. The DSA mode is however activated by providing additional channels to the on road vehicles. The process reduces the sensing time based on our proposed algorithm. The RSU should activate a threshold factor d_{th} to control the switching of DSA mode. Based on the availability in the segmented regions, the RSU estimates the number of vehicle to be allowed.

4.1.3. Energy detection

The PU state activation for a signal y being sampled at the receiving end with the sensing instances,$xth(x = 1,2,3..M)$ according to binary hypothesis algorithm

$$y(x) = \begin{cases} n(x) & for\ H_0 \\ hs(x) + n(x) & for\ H_1 \end{cases} \tag{12}$$

where $y(x)$ is the signal instance of the current vehicle being sensed. Let $s(x)$ be the SNR of PU signal and h be the amplitude gain factor of the signal. The additive noise factor considered in the signal component be $n(x)$. The system follows a Gaussian distribution with a mean of zero and variance as σ_n^2. The PU signal availability in the channel be termed as H_1 whereas its absence be denoted as H_0. The static energy test factor (Te) be denoted as

$$Te = \sum_{i=0}^{M} |y(x)|^2 \tag{13}$$

By applying central limit theorem (CLT) to the static test factor (Te) Eq.2 becomes

$$Te \sim \begin{cases} X_{2M}^2 & for\ H_0 \\ X_{2M}^2(2\gamma) & for\ H_1 \end{cases} \tag{14}$$

Here M is the total number of received samples and the term X_{2M}^2 and $X_{2M}^2(2\gamma)$ denotes the cental and non central distributions with a degree of freedom as $2M$. The non-centric parameter with γ denotes the SNR and the σ_n^2 defines the power variance function. For large values of samples as M, the CLT for the static energy test be

$$Te \sim \begin{cases} (M\sigma_n^2, 2M\sigma_n^4) & for\ H_0 \\ (M(\sigma_n^2 + \sigma_s^2), 2M(\sigma_n^2 + \sigma_s^2)^2) & for\ H_1 \end{cases} \tag{15}$$

The probabilistic calculation of the performance of the model defines the probability of estimation of available PU with a threshold value λ. The probability of detecting the available PU be P_d. The false detection probability be P_f . The performance evaluation of the energy detector is equated as

$$P_{d.ED} = Q\left(-\frac{\lambda - M(\sigma_n^2+\sigma_s^2)}{\sqrt{2M}(\sigma_n^2+\sigma_s^2)}\right) \tag{16}$$

$$P_{f.ED} = Q\left(\frac{\lambda - M\sigma_n^2}{\sqrt{2M}(\sigma_n^2)}\right) \quad (17)$$

Let the Q component introduces be the decision threshold with the noise variance as σ_n^2 and power variance as σ_s^2 . The fading and scattering effect of signal in multipath transmission is estimated using the Rayleigh fading model as

$$\bar{P}_{d.ED} = \int_0^\infty Q(\dots) f_{ray}(\gamma) d\gamma$$

$$= exp\left(-\frac{\lambda}{2\sigma_n^2}\right)\sum_{i=0}^{M-2}\frac{\left(\frac{\lambda}{2\sigma_n^2}\right)^i}{i!} + \left(\frac{2\sigma_n^2+\bar{\gamma}}{\bar{\gamma}}\right)^{M-1} * \left(e^{-\frac{\lambda}{2\sigma_n^2+\bar{\gamma}}} - e^{-\frac{\lambda}{2\sigma_n^2}}\sum_{i=0}^{M-2}\frac{\left(\frac{\lambda\bar{\gamma}}{2\sigma_n^2(2\sigma_n^2+\bar{\gamma})}\right)^i}{i!}\right) (18)$$

where $\bar{\gamma}$ be the SNR due to fading effect. The decision threshold λ can be estimated as

$$\lambda = \sigma_n^2\left(Q^{-1}(P_{f.ED})\sqrt{2M} + M\right) \quad (19)$$

The overall performance of the transmission link is measured as

$$R = \left(\frac{T-T_s}{T}\right).(1-P_f).P(H_0).CB_0 + \left(\frac{T-T_s}{T}\right).(1-P_d).P(H_1).CB_1 \quad (20)$$

Thus the noise uncertainties and scattering of signals are addressed in the proposed deep learning sensing models.

4.1.4 Proposed Deep learning Model

In this section, working mechanism of new proposed model is discussed. Even though the LSTM provides more advantages in handling the time series data. learning LSTM models for large number of memory cells becomes computationally expensive and also affects the accuracy of sensing . Hence the new hybrid deep learning model has been proposed for an effective prediction of spectrum with the less complexity.

In the proposed LOL-SM VANET Model, the mating is modeled to optimize the weight factors of the LSTM network. The lion with initial condition of randomly grouped population are initialized. The grouped lion population are assigned as $2n$ lions in the candidate population. With the best chosen weights and biases, the LSTM network is established. In the second stage, the mating process establish strong assurance of the survival of established link.

$$Offspring_j = \alpha \times Female\ Lion_j + \sum \frac{1-\alpha}{\sum_{i=1}^{NRM} Si} \times Male\ Lion_j^i \times S_i \quad (21)$$

Where $S_i = \begin{cases} 1, & if\ male\ i\ selected\ for\ mating \\ 0, & Otherwise \end{cases}$ (22)

NRM is the number of resident males in the pride of territorial space of interest.α is the random number generated.

The mutation process is took ahead with a mutation rate as 0.2 and is applied to the cubs randomly. Then in the intermittent layer, the defense operator shows the lead role of new resident male lion. The final stage is the territorial invasion which succeeds the territorial space till the optimal solution of strong terminating criteria as 100 epoch's repeats. The maximum iteration depends on the weight and bias updation to achieve optimal parameters.

4.1.5 Sensing Using Proposed Learning Model:

The sensing approach is composed of two stages. In the first stage, the energy detector is used to detect the PU signa in which the energy vectors are extracted to train the proposed model . The energy extraction method is given by

During the testing process, the proposed model identifies the PU based on the training energy vectors under dynamic conditions such as noise uncertainty and low SNR. A new threshold derived from Eq. (17) is introduced to achieve a desired probability of prediction.If the energy statistic T e < λ the final decision on the occupancy state of the PU signal will be H0. Alternatively, if the energy statistic T e ≥ λ ,no decision will be taken for sensing. The working mechanism of the proposed model is shown in the pseudocode.

Pseudocode of proposed LOL- SD VANET model

Algorithm Proposed Learning Model based Sensing	
Inputs: $\boldsymbol{\lambda_1, \lambda_T, C_{1..k} \to f_{1..k}. M. T_s. T}$	
Outputs : **decide** $\boldsymbol{H_1, H_0, \ Probability\ of\ detecting\ PU\ signal\ or\ not}$	
1:	set λ as the initial condition
2:	for m=1 to M do
3:	perform sensing on C_k with sensing interval τ using ED
4:	get Te from step 3
5:	if $Te < t$ then
6:	decide H_0
7:	elseif $Te \geq \lambda_1$ then
8:	decide H_1
9:	else if $\lambda_1 < Te < \lambda_t$ then
10:	for m=1 to M do
11:	perform sensing on C_k with sensing interval τ using OCC
12:	get $MF_y(t)$ from step 11
13:	wait for random time
14:	check the sensing time T_s
15:	if $T_s \geq \frac{1}{2}T$ then
16:	decide H_1
17:	elseif $T_s < \frac{1}{2}T$ then
18:	go to step 2
19:	end

5. Results and discussion :

Experimental setup:

In this work ,the experimentations are carried out using SUMO-OMNET in obtaining the real time vehicular data from Open street maps .For analysis different false alarm rates , the new python based Application Peripheral Interfaces(API) has been developed and implemented on Intel i7CPU, 2TB HDD , 16GB RAM ,2GB NVIDIA GPU and 2.4 GHZ operating frequency. The simulation parameters used for the experimentations are listed in the table

Parameters used	**Values**
Distribution of vehicles	Gaussian Distribution
Vehicle to vehicle Communication	IPv6 protocols
Vehicle to Infrastructure Communication	LTE
Location of RSU	1.5 Kms
Vehicle Speed	20-35 Kms

Size of the packets	100 bytes
Road Length	10 Kms
Road Lane	Two-lane Road system with all vehicles moving in same direction.

6. Simulation results:

The proposed model mentioned were trained on a real world traffic data using Adam/Softmax optimizer with the learning rate of 1e-3 learning and moving average decay of 0.9999. The training parameters for the proposed training model is listed in table

Table II Training Parameters used in the experimentation

Parameters used	Values
No of LSTM cells	05
No of Boost rounds	10
No of hidden layers	50
No of epochs used	150

As shown in table 150 epochs with 50 hidden layers and 10 boosted rounds were applied on traffic data for better spectrum prediction and .Since the proposed architecture implements the optimized LSTM predictors, weighted bias and thresholds are optimized in every iterations to obtain the minimum prediction error.

Further the performance metrics such as Accuracy, Precision and Recall are applied in training datasets and evaluated by the using the following mathematical expressions

$$\text{Accuracy} = \frac{D.R}{T} \tag{23}$$

$$\text{Precision} = \frac{TP}{TP+TN} \tag{24}$$

$$\text{Recall} = \frac{TN}{TP+TN} \tag{25}$$

Where TP and TN Represents True Positive and True Negative values and DR & T Represents Number of Detected Results and Total number of Iterations. Nearly 3500 different real time datasets under different scenario such as fading environment, vehicles' speed and noise environment. The various analysis of performance metrics of the proposed algorithm are discussed below.

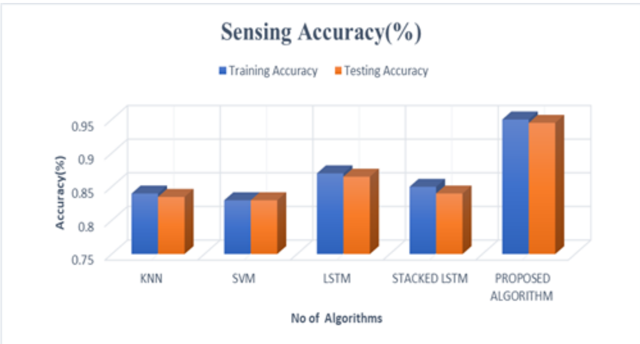

Fig 4. Comparative Analysis of Sensing Accuracy for the Proposed Algorithm with the other learning models @Rayleigh Fading Channel with Speed of 20 Km/hr

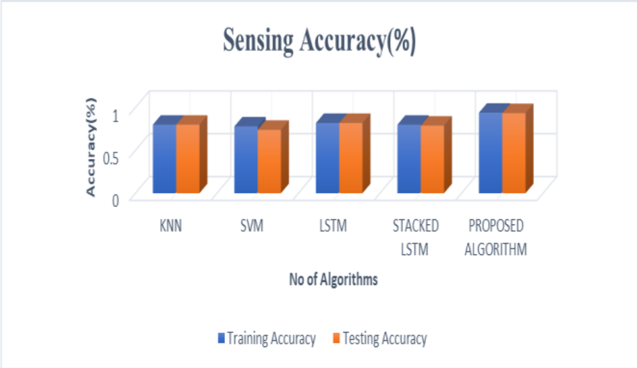

Fig 5. Comparative Analysis of Sensing Accuracy for the Proposed Algorithm with the other learning models @Rayleigh Fading Channel with Speed of 25 Km/hr.

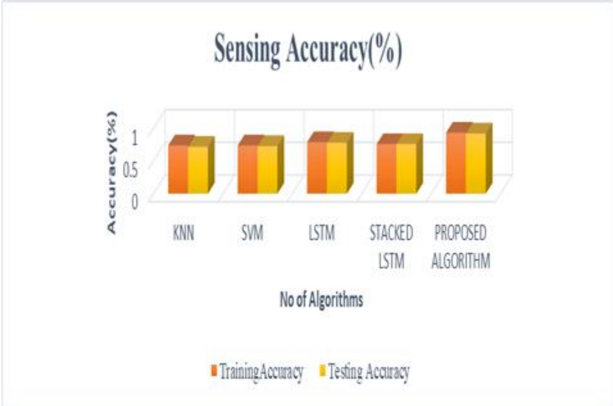

Fig 6. Comparative Analysis of Sensing Accuracy for the Proposed Algorithm with the other learning models @Rayleigh Fading Channel with Speed of 35 Km/hr

Fig 7. Comparative Analysis of Sensing Accuracy for the Proposed Algorithm with the other learning models @AWGN Channel with Speed of 20 Km/hr

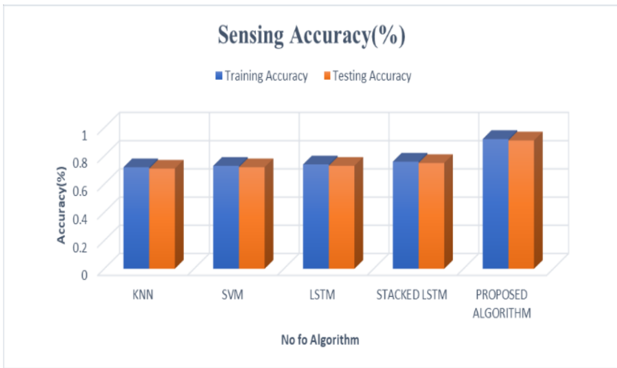

Fig 8. Comparative Analysis of Sensing Accuracy for the Proposed Algorithm with the other learning models @AWGN Channel with Speed of 25 Km/hr

Fig 9. Comparative Analysis of Sensing Accuracy for the Proposed Algorithm with the other learning models @AWGN Channel with Speed of 35 Km/hr

Figures (4)-(9), shows the comparative analysis of sensing accuracy between the different algorithms under different scenarios. From the above figure, it is evident that the proposed learning model has shown consistent performance under different speed scenarios. The sensing accuracy of the proposed algorithm is maintained from 0.935 to 0.93 under the different scenario of speed where as other algorithms has lower performance when the speed increases. The lion optimization incorporated in the deep learning algorithm leads to the stability of the prediction network whenever there is dynamic speed changes in vehicular networks. The sensing accuracy of different algorithms at AWGN channel with different speeds are shown in Figure .Again, lion optimized deep learning models has been shown persistent performance under the different scenarios and it has outperformed the other algorithms.

Table III Performance Metrics of the different algorithms at Rayleigh channel with different speeds

Algorithm	Metrics Analyzed	Channel	Speed of the Vehicles(Km/hr)		
			20	25	35
KNN	Precision	Rayleigh Channel	0.70	0.69	0.65
SVM			0.70	0.68	0.66
LSTM			0.78	0.68	0.65
Stacked LSTM			0.76	0.70	0.69
Proposed Algorithm			0.91	0.90	0.90

Table IV Performance Metrics of the different algorithms at AWGN channel with different speeds

Algorithm	Metrics Analyzed	Channel	Speed of the Vehicles(Km/hr)		
			20	25	35
KNN	Precision	AWGN Channel	0.70	0.69	0.65
SVM			0.70	0.68	0.66
LSTM			0.78	0.68	0.65
Stacked LSTM			0.76	0.70	0.69

Proposed Algorithm			0.91	0.90	0.90

Table V Performance Metrics of the different algorithms at Rayleigh channel with different speeds

Algorithm	Metrics Analyzed	Channel	Speed of the Vehicles(Km/hr)		
			20	25	35
KNN	Recall	Rayleigh Channel	0.695	0.688	0.64
SVM			0.689	0.685	0.65
LSTM			0.72	0.67	0.65
Stacked LSTM			0.70	0.69	0.69
Proposed Algorithm			0.915	0.90	0.90

Table VI Performance Metrics of the different algorithms at Rayleigh channel with different speeds

Algorithm	Metrics Analyzed	Channel	Speed of the Vehicles(Km/hr)		
			20	25	35
KNN	Recall	AWGN Channel	0.68	0.675	0.65
SVM			0.69	0.683	0.66
LSTM			0.695	0.68	0.65
Stacked LSTM			0.70	0.71	0.69
Proposed Algorithm			0.91	0.89	0.90

From the above tables, performance of the proposed algorithm has been stable as the performance of the other algorithms is low under various environmental scenarios. This shows that the optimization is required for the deep learning models for the high sensing accuracy for implementing the cognitive radio in vehicular networks.

7. Conclusion

In this paper, the proposed LOL-SM VANET model helps to intelligently decide the channels to establish an efficient transportation system. The hybrid LSTM –Lion Optimization deep learning module aids in optimal spectrum allocation to maintain good traffic flow with reduced congestion rate. The PU and SU channels are updated dynamically by the RSU to attain more efficiency. The adaptive spectrum sensing used in the proposed model reduced the fading effects than the conventional energy detection schemes. While comparing with the existing machine learning spectrum sensing models, the proposed hybrid model outperforms in terms of reduced delay, false prediction with high convergence rates. Future works include real testing of traffic management in the real scenarios

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