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RESEARCH ARTICLE

SPIKING NEURAL NETWORK-BASED NOMA-OFDM PROCESSING UNDER WEIBULL FADING FOR ACCURATE UPLINK SIGNAL PREDICTION

M. Sandhya[1, *], Aisha Banu Wahab[2], Arputha Rathina Xavier[3]

[1] Professor, School of Computer Science and Engineering, Vellore Institute of Technology, Chennai -600127.
[2] Professor, Department of Computer Science and Engineering, BSA Crescent Institute of Science and Technology, Chennai -600048.
[3]Associate Professor, Department of Computer Science and Engineering, BSA Crescent Institute of Science and Technology, Chennai -600048.
Corresponding e-mail: sandhyamagesh1997@gmail.com

Abstract – Non-orthogonal multiple access (NOMA) approach has gained popularity in recent years. Additionally, it has shown promise as a technology for wireless communication systems up to and including the fifth generation (5G). In this paper a novel Spiking Neural Network-Based NOMA-OFDM Processing Under Weibull Fading for Accurate Uplink Signal Prediction has been proposed. In the offline stage, labeled NOMA-OFDM signals are passed through a Weibull fading channel to generate training data and corresponding labels, which are then used to train the SNN for accurate prediction. In the online stage, real-time NOMA-OFDM signals undergo the same Weibull fading channel effect, and the processed signals are fed into the trained SNN to produce predictions without requiring label information. This approach enables robust channel estimation and signal detection by leveraging the adaptability and learning capability of the SNN.

Keywords *– Non-orthogonal multiple access, fifth generation, Spiking Neural Network, Signal Prediction.*

1. INTRODUCTION

NOMA-OFDM which combines the multipath fading resistance of OFDM with the spectral efficiency benefit of NOMA, has been shown to be a viable multiple access strategy for next-generation wireless networks. By allowing several users to use the same time-frequency resources, NOMA-OFDM's power domain multiplexing capability can improve throughput and connection. For diverse user contexts and massive machine-type communications, this approach is suitable for 5G and beyond. But, in the case of many user signals being sent concurrently, complicated interference patterns are formed and channel estimate and reliable recognition of the signal becomes very difficult.

The recent advances of deep learning have proven to be very effective for addressing complex, nonlinear wireless communications problems. Conventional mathematical models can only take advantage of some features of the channel, and data-driven models, such as CNN and RNN, can effectively learn the characteristics of the channel and minimize the interference without relying solely on the conventional mathematical models. A NOMA-OFDM system with deep learning can enhance the recognition accuracy of the signals and the accuracy of the channel estimate under different fading conditions. This paves the way for hybrid approaches combining learning-based and model-based approaches for improved results.

Though model-based techniques can provide analytical insight, they often fail to deal with the highly dynamic and nonlinear nature of real-world wireless channels. However, solely data-driven methods could have problems with generalisation and need large training datasets. The advantages of both approaches may be successfully combined in a hybrid deep learning framework, which uses neural networks to address model defects and physical models to direct learning. For multiuser uplink scenarios in NOMA-OFDM systems, when channel recovery and interference cancellation are crucial, this method shows the most promise.

Inter-user interference, frequency-selective fading, and noise distortion continue to make accurate CE and signal identification challenging in multiuser uplink NOMA-OFDM models. Traditional estimation methods, such as LS and MMSE, usually show performance degradation in highly dynamic channels. Furthermore, successive interference cancellation (SIC), NOMA's principal detection method, is very vulnerable to estimation errors, resulting in error propagation. As a result, there is an urgent need for an intelligent, hybrid DL model that can perform channel estimations and signal detection simultaneously while being resilient, simple, and adaptive to changing channel

conditions. The major contribution of the work has been followed by

- The primary objective is to develop a hybrid offline–online framework for efficient NOMA-OFDM signal processing.
- To simulate realistic wireless environments using Weibull fading channel modeling for improved channel estimation performance.
- To integrate a spiking neural network for adaptive and low-complexity signal prediction in dynamic conditions.
- To achieve robust joint channel estimation and signal detection in multiuser uplink NOMA-OFDM models.

The remainder of the work is divided into sections: section 2 represents the literature study, section 3 depicts the suggested technique, section 4 represents the results and discussion, and section 5 illustrates the conclusion of the proposed model respectively.

2. LITERATURE REVIEW

In 2022 Rahman, M.H., et al., [14] suggested a DNN with BiLSTM for signal identification of the first sent signal and multiuser uplink channel estimate (CE). The suggested model's performance is compared in the simulation results with that of the CNN methodology and conventional CE methods like MMSE and LS. The suggested approach is demonstrated to offer workable gains in signal-to-noise ratio and symbol-error rate, making it appropriate for 5G wireless communication and beyond.

In 2022 Gaballa, M., et al., [15] investigated the use of a Deep Neural Network (DNN) to explicitly estimate the channel coefficients of each user in the NOMA cell. Following a thorough mathematical examination of the optimisation problem, the optimal power factors are found using the Lagrange function and KKT criterion. When comparing the suggested DL model-assisted NOMA to the conventional NOMA approach, the simulation results in terms of BER, outage probability, sum rate, and individual capacity demonstrate that consistent performance can be attained even when cell capacity rises.

In 2023 Panda, B. and Singh, P., [16] proposed deep convolutional-long short-term memory (ConvNet-LSTM)-assisted receiver for signal identification in downlink NOMA systems. The proposed technique uses implicit channel state estimation to directly obtain the broadcast symbol. Furthermore, the suggested deep ConvNet-LSTM technique's robustness and superiority over previous methods are assessed.

In 2021 Xie, Y., et al., [17] created a receiver with DL assistance to identify NOMA joint signals. In end-to-end mode, the DL-based receiver simultaneously performs equalisation, demodulation, and channel estimation. When compared to the conventional signal identification approach for the NOMA scheme, the suggested deep learning strategy demonstrates a decent improvement in performance and resilience using the tapped-delay line (TDL) channel model, which is used in the 5G communication environment.

In 2022 Pandya, S., et al., [18] created a NOMA-OFDM system based on DNN to decipher the user's signals. First, training is done on the deep neural network. The simulation findings demonstrate that the deep neural network will learn the channel state information through data testing and is more resilient to symbol distortion brought on by inter-symbol information.

In 2020 Chuan, L.I.N., et al., [19] presented a CNN strategy to recover the intended signal that had been hampered by the MIMO channels. The proposed scheme can directly recover the information of a large number of users from a cluster without going through the traditional communication signal processing process, especially in the uplink NOMA scenario. The results of simulation studies in the Rayleigh channel show that the suggested learning system works better in terms of error performance than the traditional SIC detection method.

In 2020 Sim, I., et al., [20] proposed a CNN-based SIC approach to improve the multiuser and single base station NOMA schemes' performance. The suggested CNN-based SIC system can reduce the losses brought on by the SIC's flaws, in contrast to the current SIC systems. The simulation results show that the CNN-based SIC strategy may achieve good detection performance and successfully overcome the drawbacks of the traditional SIC.

3. PROPOSED METHODOLOGY

In this section a novel Spiking Neural Network-Based NOMA-OFDM Processing Under Weibull Fading for Accurate Uplink Signal Prediction has been proposed. In the offline stage, labeled NOMA-OFDM signals are passed through a Weibull fading channel to generate training data and corresponding labels, which are then used to train the SNN for accurate prediction. In the online stage, real-time NOMA-OFDM signals undergo the same Weibull fading channel effect, and the processed signals are fed into the trained SNN to produce predictions without requiring label information. This approach enables robust channel estimation and signal detection by leveraging the adaptability and learning capability of the SNN. Figure 1 illustrates the proposed methodology.

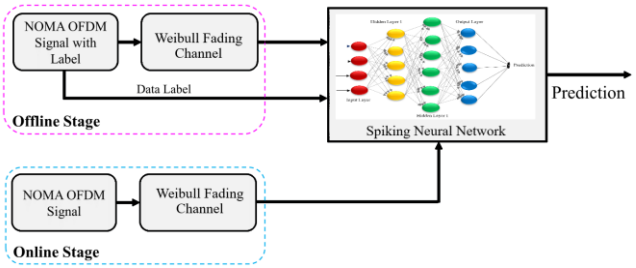

Figure 1 Proposed Methodology

3.1 Weibull Fading approach

In wireless communication systems, the Weibull fading channel is a statistical model that is used to depict small-scale fading, particularly in settings where the fading intensity is lower than that of Rayleigh fading. It is characterized by a

shape parameter β (fading severity) and a scale parameter Ω (average power). The Weibull distribution is versatile and can model fading channels with different tail behaviors by adjusting β.

$$f_R(r) = \frac{\beta}{\Omega}\left(\frac{r}{\Omega}\right)^{\beta-1} \exp\left[-\left(\frac{r}{\Omega}\right)^{\beta}\right], r \geq 0 \quad (1)$$

β>0 is the shape parameter (fading severity) and Ω>0 is the scale parameter related to the average received power. r is the instantaneous amplitude of the fading envelope. The Weibull fading model is useful in NOMA-OFDM analysis because it allows more flexibility in modeling practical channels where fading may not strictly follow Rayleigh or Rician distributions.

3.2 Spiking Neural Network

It is a network model that integrates time with neuronal and synaptic states and progressively analyses every natural neural structure. Depending on the circumstances, the activation of a neurone can alter the signal potential of neighbouring neurones. By employing a certain threshold, it activates neurones. Each brief signal that arises in the model is taken into account by spiking neurones, but they do not immediately respond to it. As soon as this happens, spiking neurones start processing the signal, which necessitates crossing a certain threshold. As a result, it generates an output signal that is either rising or dropping. Equation (2) displays the integral formula utilised in the LIF technique. I stands for current, V for voltage, C for capacitor, R for resistance, and t for time value in this equation.

$$\mathrm{I(t)} - \frac{V_m(t)}{R_m} = C_m \frac{\partial V_m(t)}{\partial t} \quad (2)$$

Although SNNs are more complicated structures than artificial neural networks (ANNs), both models have similarities. ANNs feature continuous outputs. As an alternative, it produces an incomprehensible binary output. Ultimately, it shows that each neurone only takes into account its neighbours and increases the spatial learning of spiking neurones. The neural network with spiking is shown in Fig 2.

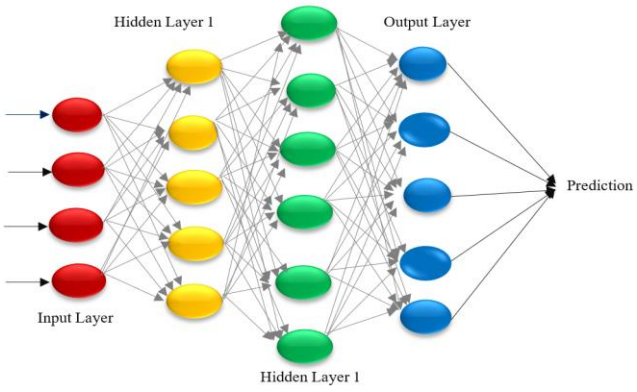

Figure 2 Architecture of Spiking Neural Network

The SNN model goes through a difficult and intricate training procedure and learns when characteristics spread across hidden layers. The last layer, which consists of completely connected layers, is where classification occurs. One popular classification technique is the Softmax function. The learnt features make use of the Softmax approach and hot coding. Every feature in hot coding has a matching class. The Softmax method is used to assign probability values to the attributes supplied to the output layer.

$$y_i = \exp(a_i) \sum_j \exp(a_j) \quad (3)$$

Spiking neural networks are built on discrete, spiking neuronal events that occur across intervals, whereas conventional neural networks emphasise intervals rather than producing values.

$$f_x(x') = R_{max} e^{\frac{\cos(\frac{2\pi}{N}(XX))}{\delta^2}} \quad (4)$$

N is the number of neurones in equation (4), where x is the input layer and y=f(x) is the output layer. In the XX coordinate, $R_{max}$is the firing rate and the number of neighbouring neurones. δ stands for a constant value.

4. RESULT AND CONCLUSION

The experimental investigation was carried out using Spyder, an Anaconda navigator operating on Windows 10 with an Intel i3 CPU clocked at 2.10GHz and 8GB RAM.

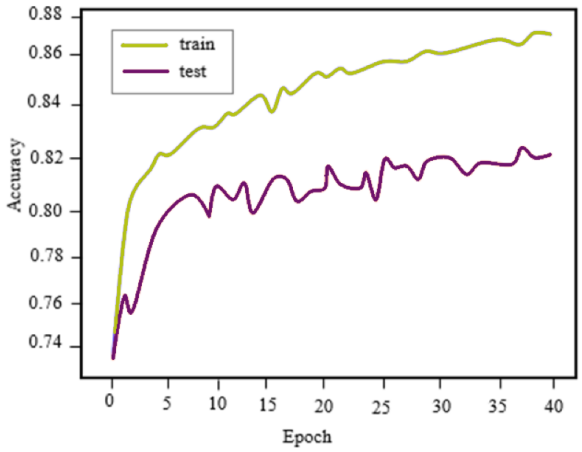

Figure 3 Training and evaluating the suggested method's accuracy

Figure 3 displays a model's accuracy throughout 40 epochs for both training and testing. The training accuracy shows constant learning, beginning at about 0.74 and increasing progressively to reach about 0.87 at the end of the era. Additionally, the testing accuracy increases quickly in the early epochs, stabilizing around 0.82 with little oscillations, indicating strong generalization with modest alterations brought on by noise or the complexity of the dataset.

Figure 4 illustrates the model's performance over 40 epochs for both training and testing datasets. The training loss starts near 0.62 and decreases steadily to around 0.28, indicating effective learning and improved fit to the training data. The testing loss also shows a downward trend that plateaus at a higher value (~0.42) with some fluctuations that may be attributed to the fluctuations in the test data set or slight overfitting.

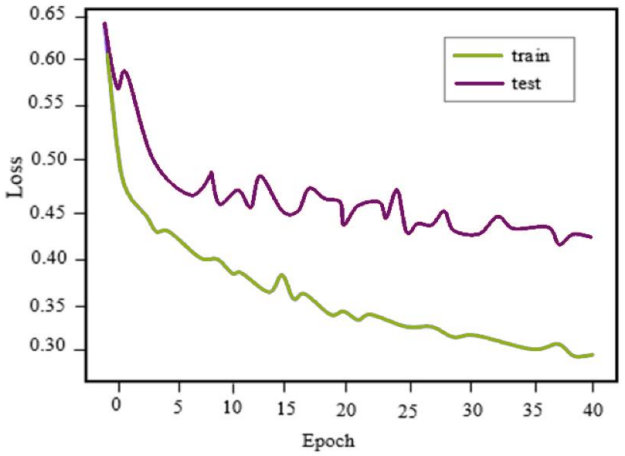

Figure 4 Training and Testing loss of proposed method

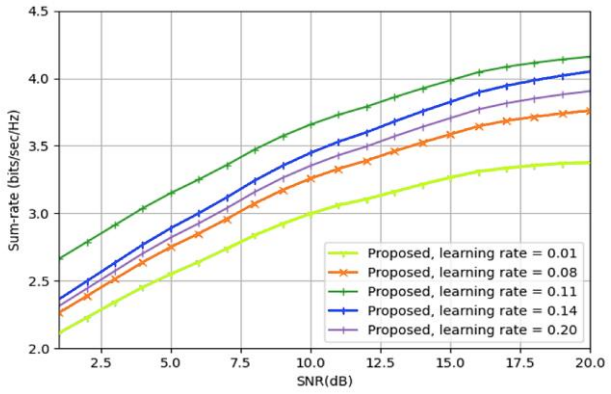

Figure 5 Sum rate versus SNR for the proposed model

Figure 5 shows the sum-rate performance in bits/sec/Hz versus SNR in dB of the proposed system for different learning rates. For all configurations, the sum-rate increases as SNR increases from 2 to 20 dB, suggesting that increasing SNR results in more data being transmitted. The learning rates that yield the best overall results are 0.11, 0.14, and 0.20, which are very close, with 0.01 producing the least desirable results. The trend indicates that having an optimal learning rate is highly beneficial for the sum-rate efficiency in the proposed framework, more particularly in moderate-to-high SNR regions.

Figure 6 illustrates the MSE performance versus SNR for different batch sizes during training. The larger the batch size, the more SNR the higher, the more accurate the estimation.The higher SNR the more accurate the estimation, as it is seen as SNR increases from 5dB to 30dB, the MSE decreased consistently for all batch sizes. At higher SNR, smaller batch sizes (e.g., 10, 20) quickly converge towards larger batch sizes, and the MSE is initially high for small batch sizes. As can be seen, batch size 50 performs well at all SNR values, and batch size 100 performs competitively with regard to accuracy, especially at low-to-mid SNR values.

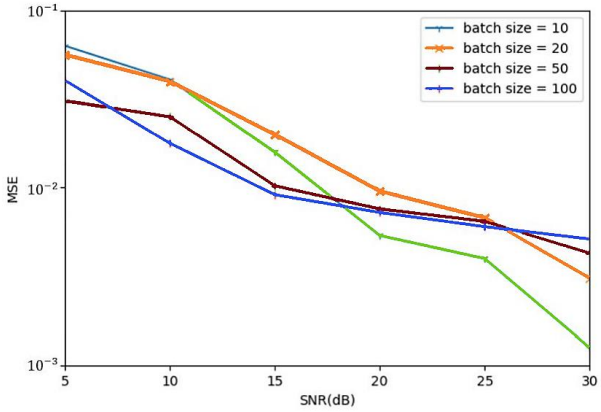

Figure 6 Comparison of MSE vs SNR

5. CONCLUSION

In this research a novel Spiking Neural Network-Based NOMA-OFDM Processing Under Weibull Fading for Accurate Uplink Signal Prediction has been proposed. During the offline stage, these labeled NOMA-OFDM signals should be fed into a Weibull fading channel for the generation of training data and labels, and then the trained SNN is used to predict the signals accurately. During the online stage, the fading channels effect of real-time NOMA-OFDM signals is the same as the offline stage, and the processed signals are used to predict the fading channels effects without the need for label information with the trained SNN. Such an approach helps achieve strong channel estimation and signal detection, taking advantage of the flexibility and learning ability of the SNN. Future research under single input, multi output (SIMO) or multi input, single output (MISO) with various modulation schemes and fading channel types might further investigate the performance of the suggested model.

CONFLICTS OF INTEREST

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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AUTHORS

M. Sandhya Magesh is working as a Professor in School of Computer Science & Engineering in Vellore Institute of Technology, Chennai Campus. With over twenty-five years of experience, she has published around 75 papers in reputed International Conferences and journals like IEEE Access, Wireless Personal Communications, Arabian Journal of Science and Engineering, etc. She is a powerful force in the workplace and uses her positive attitude and tireless energy to encourage others to work hard and succeed. Her research interests include Health Care Applications, Wireless Security, RFID, Data Analytics.

W. Aisha Banu Wahab is a Professor and Head of the Department of Computer Science and Engineering at B. S. Abdur Rahman Crescent Institute of Science and Technology. She has been serving in the institute since 1997, with over two decades of academic and research experience. She holds a Ph.D. in Computer Science and Engineering from Anna University, Chennai. Her areas of expertise include Cloud Computing, Social Network Analysis, Information Retrieval, and Big Data. She has published more than 68 research papers in reputed journals and international conferences. She has successfully guided 6 Ph.D. scholars in various domains of Computer Science. Dr. Aisha Banu has been involved in multiple funded consultancy and research projects. She has organized and participated in numerous FDPs, workshops, and national conferences. She has served in key administrative roles such as NBA Coordinator, Research Supervisor, and ISO Auditor. She is also a member of the Board of Studies and Academic Council at the institute.

Arputha Rathina Xavier is currently Associate Professor in the Department of Computer Science and Engineering, B.S.Abdur Rahman University. She has been working in this Institution for the past 25 years. Her area of interest includes Image Processing, Human Computer Interaction and Emotional Intelligence. She has guided more than 40 UG and 25 PG projects. She has visited Hiroshima University - Japan, to acquire the basic knowledge on Kansei Engineering. She did her thesis in the area of Emotion detection using Facial expressions and Speech. She is a member of ACM and IEEE.

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RESEARCH ARTICLE

HYBRID OPTIMIZATION USING ENERGY EFFICIENT CLUSTER FORMATION AND ROUTING IN WIRELESS SENSOR NETWORKS

P. Tamilselvi[1, *], J Sworna Jo Lijha [2]

[1] Associate Professor, Department of Electronics and Communication Engineering, Sree Sakthi Engineering College, Karamadai, Coimbatore, Tamilnadu, India.

[2] Associate Professor, Department of Electronics and Communication Engineering, Sree Sakthi Engineering College, Karamadai, Coimbatore, Tamilnadu, India.

[*]*Corresponding e-mail: dr.tamilselvip2024@gmail.com*

Abstract –Wireless Sensor Network (WSN) is an interconnected sensor node that can connect and communicate with one another to collect and transmit data from their surroundings. However, the existing technique has high delay, low network lifetime and energy consumption. To address these issues, a novel Hybrid Optimization using Energy Efficient Cluster Formation and Routing in Wireless Sensor Networks (HOER). Initially, C Means clustering is employed in the proposed framework to improve cluster formation. The Artificial Bee Colony Optimization (ABCO) provides an effective way for cluster head selection (CHS) based on node degree, energy consumption and normalization. Consequently, the Ant Colony Optimization (ACO) is utilized to find a routing path between the source and the destination over the cluster head. The proposed model was compared to existing techniques on energy consumption, throughput, Alive Node, delay and network lifetime are used. The proposed HOER achieves the higher network lifetime by 95.8% for proposed and 48.17 %, 39.17 % and 20.25% than the RK-EFCRP, DOS-RL and EPFMR approaches.

Keywords *– Wireless Sensor Network, C-means Clustering, Artificial Bee Colony Optimization, Ant Colony Optimization, cluster head selection, Energy-Efficiency and routing.*

1. INTRODUCTION

The WSN comprises of tiny low-power sensor nodes that monitor and gather data from their surroundings before sending it to a central base station for processing and analysis. Each node consists of a sensing unit, a processing unit, a transmission unit, and a power unit, and it is in charge of data collecting, processing, and communication with other nodes. WSNs organize themselves and form multi-hop networks to transfer data efficiently over long distances. Sensor nodes operate on limited battery power, so conserving energy is very important. The application of various methods like clustering, data aggregation, load balancing, and scheduling results in less energy consumption, better workload management, and longer network lifetime. Through the process of clustering, nodes are classified with a Cluster Head that gathers information from other nodes, processes it, and transmits it to the base station, thereby minimizing the consumption of energy and communication throughput. WSNs operate in harsh and remote areas. Replacing or recharging batteries is quite challenging while continuous monitoring and data delivery are maintained.

Routing in WSN is the process of finding the path of sensing data from sensor nodes to the base station. In small networks, single-hop communication is possible between nodes and a base station. Large-scale networks desire for multi-hop communications, in which all nodes send and forward data from other nodes. Routing should take into account the restricted energy supply, processing capacity, and memory of the sensor nodes, and it should prioritize energy conservation, delay reduction, and prolongation of the network's lifetime. Routing protocols should be designed in such a way that they can achieve load balancing, hence, preventing the over-use of a single node which might lead to the node being drained of energy rapidly. They will also adapt to network topology changes, such as node failures or the addition of additional nodes. The routing function must be non-scalable in the sense that it cannot handle networks with thousands of nodes while also providing reliable data delivery in both dense and wide areas.

WSNs depend on batteries, which makes energy management very important to prolong the network life and also to guarantee the receipt of reliable data. Power shortage remains a very serious issue, more particularly in demanding environments like battle zones or isolated observation locales. Sensor nodes' performance degrades at the low battery power levels, which can potentially lead to network failure or data loss. The energy issue is extremely vital to be tackled, as the power sources of nodes are limited and battery changing or recharging is not always easy. A WSN may consist of millions of energy-limited nodes therefore energy management must be done very meticulously in order for the network to function properly and efficiently.

- The primary objective of the work is developed a novel Hybrid Optimization using Energy Efficient Cluster Formation and Routing in Wireless Sensor Networks.
- C means clustering is used to improve cluster formation.
- Artificial Bee Colony Optimization gives an effective approach for CHS based on node degree, energy consumption, and normalization.
- The Ant Colony optimization method is used for routing between source and destination.
- The proposed model was compared to existing techniques on energy consumption, throughput, Alive Node, delay and network lifetime are used.

The content of the paper is organized as: Section 2) explains the literature survey, Section 3) discusses the proposed methodology and its working process, and Section 4) Results & discussion Finally, section 5 concludes the paper.

2. LITERATURE REVIEW

Recent advancements in WSN have significantly improved the ML and DL models for improving energy efficiency and network life time. This literature review explores current approaches in clustering in WSN. Some of the most recent approaches are discussed in this section.

In 2023, Pedditi, R.B., and Debasis, K. [14] suggested an energy-aware Internet of Things (IoT)-based WSN model for forest fire monitoring that uses an efficient clustering and routing approach. Traditional forest fire detection technologies and current WSN-based systems are inefficient for real-time monitoring of huge forest regions. The proposed EERP protocol minimizes overall energy usage while improving the routing of forest fire detection devices. Simulation results suggest that current MAC protocols can reduce sensor node energy usage while boosting overall network performance.

In 2025, Hussain, M., et al. [15] suggested an improved Rank-Based Key Management for Energy-Efficient Cluster-Based Routing Protocol (RK-EFCRP). Existing WSN routing techniques fail to combine energy economy, security, and dependable data transfer. The proposed RK-EFCRP method utilizes an adaptive clustering approach, which leads to energy consumption reduction and at the same time, security, data dependability, and latency enhancements. Experimental outcomes indicate that RK-EFCRP is superior to the current protocols, including Safety-RPL, HBEER, SEHR, and SEAMHR in terms of various important performance indicators.

In 2023, Godfrey, D. et al. [16] introduced an energy-efficient multi-objective routing strategy in light of the Reinforcement Learning with Dynamic Objective Selection(DOS-RL) strategies. Traditional routing techniques are unable to cope with the network changes occurring dynamically in an efficient manner, leading to high latency and poor performance of the network. The suggested DOS-RL routing ability offers a well-balanced performance continuum consisting of energy saving, reliability, and adjustability, thus making it appropriate for changing and enormous IoT scenarios. Simulation findings show that the DOS-RL protocol performs much better than classic routing protocols like OSPF and SDN-Q.

In 2022, Mehbodniya, A., et al. [17] suggested an Energy-aware Proportional Fairness Multi-user Routing (EPFMR) framework for WSNs. Existing method doesnot provide effective routing procedures that conserve energy during route finding and data transfer. The EPFMR framework substantially decreases energy usage during routing, shortens route search time, and increases throughput. The simulation results show EPFMR outperforms current state-of-the-art approaches.

In 2022, Jaffri, Z.U.A., et al. [18] developed a Threshold-based Energy-aware Zonal Efficiency Measuring (TEZEM) hierarchical routing system for next-generation WSN. Hierarchical routing techniques fail to increase network lifetime, resulting in wasteful energy use, decreased stability, and poorer throughput. The proposed TEZEM protocol increases energy efficiency by efficiently controlling network traffic using zonal divisions and threshold-based data transfer. The simulation results show that the TEZEM protocol with 9 zonal divisions has the maximum stability and throughput.

In 2022, Dogra, R., et al. [19] introduced a new routing protocol called Enhanced Smart Energy-Efficient Routing Protocol (ESEERP) intended to make WSN-IoT scenarios more energy-efficient and to extend their lifetime. The integration quality of WSNs into IoT fails due to high consumption of energy and limited network lifespan. ESEERP deduces the number of sensor nodes needed to sleep for better energy preservation, efficient route mechanism, and higher bandwidth utilization. Simulation result show that ESEERP outperforms other approaches, including Genetic Algorithm, Ant Lion Optimization, and Particle Swarm Optimization.

In 2024, Kumar, N., et al. [20] developed a Hybrid Whale-Ant Optimization Algorithm (WAOA) for energy-efficient routing in WSNs. Existing approaches do not maximize CHS and data routing at the same time, resulting in inferior network efficiency and shorter lifetime. The WAOA algorithm successfully balances energy consumption and routing efficiency by optimizing both CHS and data pathways. According to the performance analysis, WAOA beats existing approaches such as MOORP, MMABC, and AZEBR in terms of network lifespan by 5.78%, 16.11%, and 18.52%, respectively.

3. PROPOSED METHODOLOGY

In this section, a novel Hybrid Optimization using Energy Efficient Cluster Formation and Routing in Wireless Sensor Networks (HOER) has been proposed. Initially, sensor nodes are first grouped into clusters. C Means clustering is used to improve cluster formation. then, the ABCO algorithm is introduced as an effective method for selecting cluster heads based on node degree, energy consumption and normalization. Then ACO algorithm is utilized to routing path between the source and the

destination across the CHS. Figure 1 shows the proposed methodology.

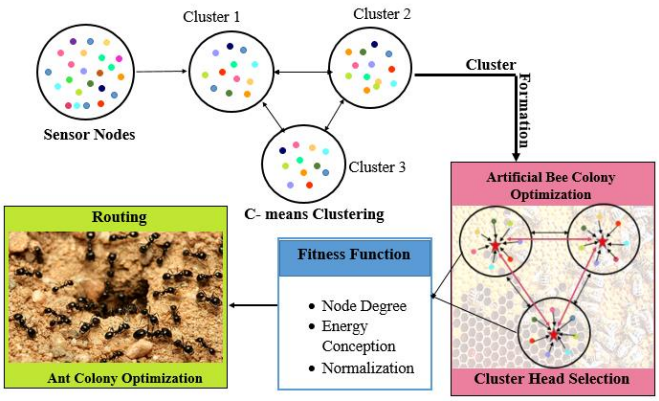

Figure 1: Proposed Methodology

3.1 Cluster Formation via C-means Clustering

In this section, C-means clustering is used for cluster formation. C-means is an unsupervised clustering technique that partitions data samples into *C* distinct clusters based on feature similarity. It is widely adopted due to its simplicity and effectiveness. However, one major drawback of this method is that the number of clusters must be predefined, which may not be optimal for datasets with unknown or varying structures. Hence, there is a need for clustering approaches that can adaptively determine suitable cluster configurations.

The objective function of the C-means clustering algorithm is given by:

$$M_{FCJ}(V,U) = \sum_{i=1}^{n} \sum_{i=1}^{C} V_{JI}^{A} \left\| Y_J - U_I \right\| \quad (1)$$

$$T.s \sum_{i=1}^{n} v_{ji} = 1, i = 1, \ldots, N \quad (2)$$

FCM can only assign one sample to an imprecise cluster, it is difficult to produce appropriate results for some samples that overlap between several clusters.

$$J_{MCN^{T,I,K,U)}} = \sum_{J=1}^{N} \sum_{I=1}^{C} \{\varpi_1 T_{ij}\} \| Y_J - U_I \|_2 \quad (3)$$

$$T.s \sum_{i=1}^{n} T_{ij+y_{j+k_j}} = 1,0 < T_{ji}, Y_J K_I < 1 \quad (4)$$

$J_{MCN}$is the inaccurate cluster center for y_j,and δ is a parameter to detect outliers. The weight factors are $\varpi 1$, $\varpi 1$, and $\varpi 3$; $\beta$is the same as MCN.N

$$u_i = \frac{\sum_{J=1}^{n} (\varpi_1 K_{ji})\ y_j}{\sum_{J=0}^{n} (\varpi_1 K_{ji})} \quad (5)$$

The support degree of Y_i to the accurate cluster is represented by y_j, Whereas the support degree of y_j . the support degree of y_i to outliers is shown by k_{ji} .

3.2 Artificial Bee Colony Optimization

In this part, Artificial Bee Colony Optimization (ABCO) is utilized to choose cluster heads. Bees that were waiting for the food source (FS) selection in the dance area were regarded as observers; bees that foraged at random were called scout bees; The hired bees returned to a FS they had just visited.

Initialization: Let us assume that SN is the population size required when we want to find the population variance. $X_i = \{X_{i1} X_{i2,\ldots} X_{id}\}$ $(i = 1,2,\ldots,n)$, The problem is to optimize the dimension vector d. Thus, the first population is formed at random.

$$X_i = X_U + rand(0,1).(X_U - X_L) \quad (6)$$

Population Updating: The FS location is initialized randomly and each forager bee is associated randomly with a FS. Every worker bee recognizes and examines another adjacent FS near the one it worked on previously.

$$\text{(i)} \qquad V_{ij} = X_{ij} + rand(-1,1).(X_{ij} - X_{kj}) \quad (7)$$

where V_{ij} is the candidate food position, k∈{1, 2, 3... SN}, j∈{1, 2, 3,..., d}, and rand (−1,1) is the numerical value around randomly generated (−1, 1).

Bee Source Selection: In this phase, the spending level of the source determines how bees are there to fly. which are determined by their fitness values. With the equation, they will be pushed toward FS that generate significant profits:

$$\text{(ii)} \qquad p_i = \frac{fit(X_i)}{\sum_{n=1}^{SN} fit\ (X_i)} \quad (8)$$

where f (X_i) represents the fitness function of the n-th solution, which is proportional to the amount of nectar available to the FS $n \in \{1, 2, 3, \ldots, SN\}$.

$$fit_{(X_n)} \begin{cases} f\frac{1}{(X_n)}, f(X_n) \geq 0 \\ 1 + abs\left(f(X_n)\right), f(X_n) < 0 \end{cases} \quad (9)$$

Where $f(X_n)$ is the objective function value corresponding to the bee source X_n following bees are roaming the area around the source, thus augmenting the local availability of the algorithm.

3.3 ANT Colony Optimization Via Routing

In this part, the selected cluster head is used to find the shortest path using Ant Colony Optimization (ACO). ACO is a nature-inspired algorithm based on the communication methods used by ant colonies. Individual ants communicate through the use of pheromone trails in a form of indirect communication.

$$\eta ij = \begin{cases} -\log CFP(\{e_{i,j}\}) \\ 0, \qquad else. \end{cases} \quad (10)$$

The pheromone setting is mostly governed by the rules of the Max-Min Ant System. In order to reduce the chance of getting stuck in local maxima, after the first iteration the pheromone levels will be limited to be between two values calculated from the best solution that we have encountered.

$$\tau_{max} = \frac{f_{gb}}{b}(1 - \rho) \quad (11)$$

$$\tau_{min} = \in . \tau_{max} \quad (12)$$

We only distribute pheromones on the best path taken within the given iteration.

$$\tau_{ij} = \rho . \tau_{ij}^{(t-1)} \quad (13)$$

On the best route found, the pheromone update is described with Eq. (), the negative logarithm of the probability of the given path failing is considered:

$$\tau_{ij}^{(t)} = \rho.\tau_{ij}^{(t-1)} - \log(A(P)) \quad (14)$$

$$p(i,j) = \frac{(\tau ij)^{\alpha}(\eta ij)^{\beta}}{\sum_{u_q \in n_i((\tau ij)^{\alpha}(\eta ij)^{\beta}} ,\text{if } u_j \in n_i \quad (15)$$

All ants are put at the beginning position s. They select the next node based on heuristics and pheromone levels. Nodes can only be visited once, and the last visited node must be t. If an ant fails to reach the destination, no path will be returned.

4. RESULT AND CONCLUSION

In this section, the efficacy of the suggested technique is assessed using matlab-2022b, performance analysis is discussed regarding various calculation metrics such as Residual Energy, Alive Node, Cluster Stability, throughput, and end to end delay. The PC requirements for this experiment comprised an i9-9820X 3.30 GHz CPU, 2 TB of RAM, and Ubuntu 20.04.1 LTS. The proposed model efficacy is contrasted with RK-EFCRP [15], DOS-RL [16], EPFMR [17] respectively.

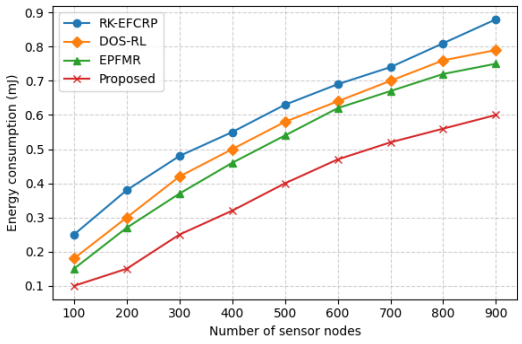

Figure 2: Energy consumption

Figure 2 shows comparison of Energy consumption via number of sensor nodes. The proposed model has lower energy consumption compared to existing techniques such as RK-EFCRP, DOS-RL and EPFMR. When a node is 300, the energy consumption of the proposed model is 0.25 mJ and the existing RK-EFCRP, DOS-RL and EPFMR yield 0.48 mJ, 0.42 mJ and 0.37mJ respectively. The proposed model lower by 37.3 mJ, 35.1 mJ and 27.5 mJ than the existing techniques.

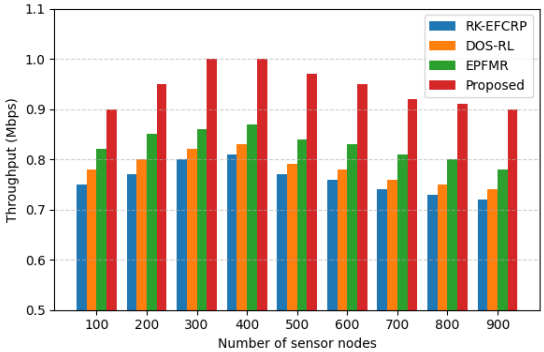

Figure 3: Throughput

Figure 3 illustrates Comparison of Throughput via number of sensor nodes. The suggested model has higher than the existing techniques such as RK-EFCRP, DOS-RL and EPFMR. When the node is 200, the throughput of the suggested model is 0.95 Mbps, and the existing RK-EFCRP, DOS-RL and EPFMR yield 0.76 Mbps, 0.8 Mbps and 0.85Mbps respectively. And when the node is 600, the throughput of the suggested model is 0.96 Mbps, and the existing RK-EFCRP, DOS-RL and EPFMR yield 0.94 Mbps, 0.77Mbps and 0.75Mbps respectively. The proposed model higher by 24.0 Mbps, 20.2Mbps and 13.0Mbps than the existing techniques.

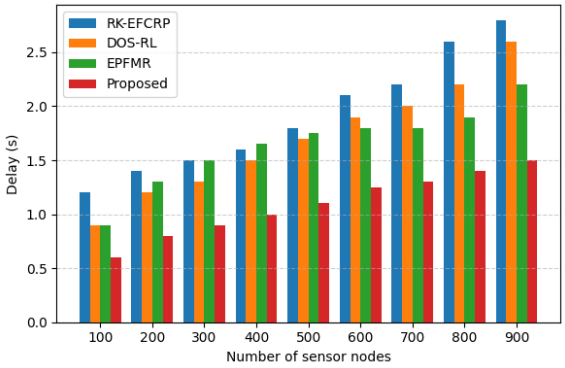

Figure 4: Delay

Figure 4 show the Comparison of Delay via number of sensor nodes. The suggested model has lower than the existing techniques such as RK-EFCRP, DOS-RL and EPFMR. When the node is 400, the delay of the suggested model is 1.0 s, and the existing RK-EFCRP, DOS-RL and EPFMR for the 1.54 s, 1.5 s, and 1.55 s respectively. The proposed model lower by 43.5 s, 39.8 s and 36.6 s then the existing techniques.

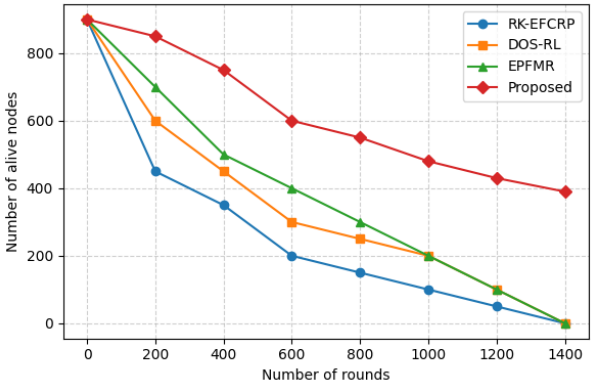

Figure 5: Alive node

Figure 5 shows the Comparison of alive node via number of sensor nodes. The suggested model is higher than the existing techniques such as RK-EFCRP, DOS-RL and EPFMR. When the node is 800, the alive node of the suggested model is 576% and the existing RK-EFCRP, DOS-RL and EPFMR for the 182%, 225% and 310% respectively. The proposed model higher by 20.2%, 29.4% and 34.6% then the existing techniques.

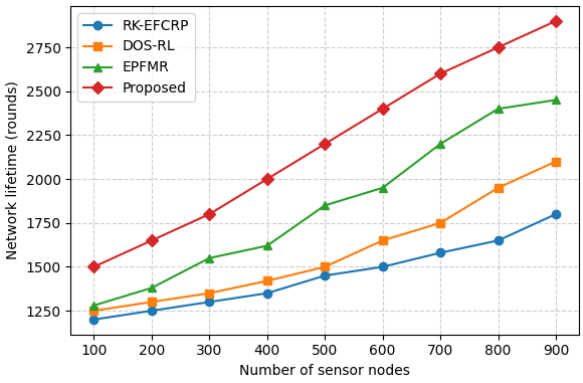

Figure 6: Network lifetime

Figure 6 displays the Comparison of network lifetime via number of sensor nodes. The proposed model is higher than the existing techniques such as RK-EFCRP, DOS-RL and EPFMR. When the node is 100, the alive node of the proposed model is 1500 and the existing RK-EFCRP, DOS-RL and EPFMR for the 1230 rounds (r), 1250 r and 1340 r respectively. The proposed model higher by 59.0 r, 67.3 r and 78.0 r then the existing techniques.

5. CONCLUSION

This paper proposed, a novel Hybrid Optimization using Energy Efficient Cluster Formation and Routing in Wireless Sensor Networks (HOER) has been proposed. Initially C Means clustering is used to improve cluster formation and reduce communication costs. The proposed HWEL techniques mainly uses the ABCO approaches to select cluster head. The ACO utilized best route path from source to destination, then cluster head uses the best route to send data to the base station. Proposed HOER framework achieves network lifetime by 95.8% for proposed then 48.17 %, 39.17 % and 20.25% than the RK-EFCRP, DOS-RL and EPFMR approaches. Future research will extend the HOER framework to mobile and large-scale wireless sensor networks with dynamic topology variations. Machine learning-based intelligence and security-aware mechanisms can be incorporated to enable adaptive cluster formation and secure routing decisions under changing network conditions.

CONFLICTS OF INTEREST

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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AUTHORS

TamilSelvi. P is an accomplished academician, researcher, and Associate Professor in the Department of Electronics and Communication Engineering with over 12 years of teaching experience in reputed engineering institutions. She is currently serving at Sree Sakthi Engineering College, Karamadai, where she actively contributes to teaching, research, student mentoring, and academic development. She obtained her Ph.D. in Wireless Sensor Networks from Alagappa Chettiar Government College of Engineering and Technology, Karaikudi, and completed her M.E. in Applied Electronics with First Class with Distinction from Anna University, Coimbatore. She also earned her B.E. in Electronics and Communication Engineering with First Class with Distinction from Bannari Amman Institute of Technology, Sathyamangalam. Her research interests include Wireless Sensor Networks, Artificial Intelligence, Machine Learning, Digital Signal Processing, Optical Communication, Embedded Systems, and Electronic Devices. She has published several research papers in reputed SCI, Scopus, IEEE, and international journals, and has presented her work at national and international conferences. Her research contributions focus on energy-efficient routing protocols, deep learning applications, healthcare monitoring, network security, and intelligent communication systems. Dr. Tamil Selvi is the holder of three patents in the areas of power systems, wireless sensor networks, and AI-based damage detection technologies. She is currently pursuing several high-impact research projects leading to SCI publications in artificial intelligence, medical image analysis, and intelligent communication networks. She has also collaborated on funded research projects in Wireless Body Sensor Networks. Apart from teaching and research, she has played a significant role in coordinating NBA accreditation activities, international conferences, workshops, seminars, faculty development programmes, and hands-on technical training. She is proficient in software tools including MATLAB, Python, NS-2, ORCAD PSpice, ModelSim, and Xilinx, and is committed to promoting industry-oriented learning and innovation among students. Dedicated to academic excellence and lifelong learning, Dr. P. Tamil Selvi strives to inspire students through quality education, research-driven teaching, interdisciplinary collaboration, and the effective integration of emerging technologies into engineering education.

Sworna Jo Lijha J is an Assistant Professor in the Department of Electronics and Communication Engineering at Sree Sakthi Engineering College, Coimbatore, Tamil Nadu. She began her academic career in 2015 as an Assistant Professor at Arunachala College of Engineering for Women, Manavilai, Tamil Nadu, and has since contributed to teaching, student mentoring, and academic development. She received her B.E. degree in Electronics and Communication Engineering and her M.E. degree in Communication Systems from Anna University, Chennai, in 2013 and 2015 respectively. She is currently pursuing her Ph.D. under the supervision of Dr. N. Muthukumaran. Her research interests include deep learning, low-light image processing, and medical image processing. Through her ongoing doctoral work, she aims to advance innovative solutions in intelligent imaging systems and healthcare applications. Dedicated to academic excellence and lifelong learning, Sworna Jo Lijha J strives to inspire students by integrating emerging technologies into engineering education and fostering research-driven teaching practices.

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RESEARCH ARTICLE

HONEYPOT-ENABLED INTRUSION DETECTION USING OPTIMIZED DEEP LEARNING IN IOT DEVICES

Jeya S Shemona[1, *], Sree Arthi D

[1] Assistant Professor, Department of Electronics and Communication Engineering, Sree Sakthi Engineering College, Karamadai, Coimbatore, Tamil Nadu, India.

[2] Department of Electronics and Communication Engineering, Sree Sakthi Engineering College, Karamadai, Coimbatore, Tamil Nadu, India.

[*]*Corresponding e-mail: jeyashemona.ss@gmail.com*

Abstract – Internet of Things (IoT) based methods have enhanced operations on several applications in the recent year. Cyber-attacks are made more likely by inadequate security protocols in the Internet of Things network. This paper proposed a Honeypot enabled Intrusion Detection using Optimized deep Learning (HIDOL) technique to identify the attack on IoT device. Initially, a honeypot server is placed to find malevolent activity in IoT devices and the patterns are gathered from the attacker. The necessary data are extracted during the feature extraction procedure using a one-hot encoder. By using the Dingo Optimization, the essential features are selected. The Conv-BiLSTM model will classify the vulnerabilities like DDoS attacks, physical attacks and Ransomware attacks. The KDDCUP 19 dataset are used to evaluate the suggested system's efficiency and the evaluation measures like Throughput, Detection Rate and Time efficiency have been utilized to assess the efficacy of the suggested intrusion detection technique. By the comparison analysis the proposed HIDOL archives detection rate of 28.07% which is comparatively higher than the existing system respectively.

Keywords *– Internet of Things, Intrusion Detection, One-hot Encoder, Conv-BiLSTM.*

1. INTRODUCTION

In this modern world the Internet of Things is being used in more sectors. The Internet of Things (IoT) is transforming everyone's lives by offering services like controlling and monitoring connected smart devices [8]. It is a relatively new technology that connects items to the internet to enhance and support people's lives, occupations, and cultures [9]. IoT devices are vulnerable to several possible security issues since they are connected to the internet via immature and insecure communication protocols and software [10]. By utilizing the IoT basic technologies, such as communication technologies, embedded devices, Internet protocols, pervasive and ubiquitous computing, sensor networks, and AI-based applications, gadgets can become smart objects [11]. The main objective is to connect everything so that computers can all become intelligent, programmable devices and more secure means of communicating with one another [12].

Honeypots are a sophisticated software agent and useful instruments for apprehending malevolent attackers. Honeypots are a viable option because they offer useful information about the attackers. A device designed to be attacked and compromised is called a honeypot. With the use of honeypots, hackers are tricked into believing they have physical access to systems [13]. Honeypots can be broadly divided into two types: research honeypots and producing honeypots. Which protect an institution, and research honeypots, which are mostly employed for educational purposes [15]. This study's primary objective is to use honeypots to record attacks on Internet of Things devices. These days, honeypots are available in many shapes and sizes and can be used for a number of purposes. Depending on the degree of involvement with the attacker, it might be categorized [14].

A cyber-attack is a criminal act that interferes with computers and computer networks in order to compromise the security and privacy of individuals and organizations [16]. There are several types of attacks that can be made against different networks using compromised services, including DDoS attacks, Brute force attacks, physical attacks, and ransomware attacks [17]. Attacks have increased everywhere in the world, including in India. Approximately 49,000 cybercrimes were recorded in India in 2018. When it surpassed the 2-lakh barrier in 2020, it saw its first notable surge. In 2021, there were 28 times as many cybercrimes, exceeding the 14-lakh mark [18]. Therefore, a novel, Honeypot enabled Intrusion Detection using Optimized deep Learning (HIDOL) technique have been introduced to maintain the privacy of IoT devices. The suggested work's primary contribution is as follows.

- Initially, a honeypot server is placed to find malevolent activity in IoT devices and the patterns are gathered from the attacker.
- The necessary data are extracted during the feature extraction procedure using a one-hot encoder. By using the Dingo Optimization, the essential features are selected.
- The Conv-BiLSTM model will classify the vulnerabilities like DDoS attacks, physical attacks and Ransomware attacks.
- Finally, the efficiency of the proposed system is assessed using the KDDCUP 19 datasets, and assessment metrics such as Throughput, Detection Rate and Time efficiency are utilized to determine the efficiency of the suggested method in intrusion.

2. LITERATURE REVIEW

In recent years, several research have employed various methodologies to detect intrusions in Internet of Things devices. A few contemporary evaluation techniques and the issues they raise are covered in the section that follows. These are listed in the following order:

In 2020 Pashaei, et al. [1] proposed an industrialized Early Intrusion Detection System (EIDS) to change the Intrusion Detection System (IDS) method. The EIDS, which provides cyber-attacks and industrial network systems protection against vulnerabilities, instantly notifies heads of industrial network security. The attack attains a 98.72% accuracy rate. Improving the security of the IoT environment involves some dangers, which is one of the main disadvantages.

In 2021 Ashiku, and Dagli, [2] suggested a deep learning architecture to create a durable and adaptable intrusion detection system (IDS) that can identify and categorize network threats. Deep neural networks (DNNs) can enable adaptive IDS with the ability to learn to identify recognized. The drawbacks of the detection approach result in slow networks, higher CPU consumption, false positives, and false negatives. For the repartitioned and user-defined multiclass classification, the suggested method yielded an overall accuracy of 95.4% and 95.6%, respectively.

In 2022 Pashaei, et al. [3] proposed a state-action-reward-state action (SARSA) Markov Decision Process (MDP) for honeypot design. By collecting aggressive behaviour, the suggested strategy raises the bar for early honeypot identification. This method archives a highest accuracy rate of 98.15%. Future research trends include the use of alternative RL approaches in conjunction with metaheuristics, which can significantly cut learning time.

In 2020 Chakkaravarthy, et al. [4] proposed a robust Intrusion Detection Honeypot (IDH) to address the cyber-attacks. In a secure test, the suggested IDH is experimentally tested using over 20 different versions of new ransomware. The suggested IDH outperforms an accuracy rate of 96.99% in the ransomware detection system. In future the IDH with transfer learning capabilities will eventually be able to optimize the load on devices with limited resources.

In 2023 Soltani, et al. [5] proposed a framework for deep learning-based IDS to address upcoming attacks. This model is the initial one in the security sector that uses combination of deep novelty-based classifiers and conventional clustering based on the specialized layer of deep structures. This model has an accuracy of 99.85% across the majority of attack types.Future research focus to improve the method based on anomaly traffic.

In 2020 Kaur, and Singh, M, [6] proposed method for signature generation and hybrid intrusion detection based on deep learning. The suggested system detects attacks proactively and efficiently generates signatures, minimizing the harm caused by network attacks. With an accuracy of 99.40% for CICIDS and 99.27% for NSL-KDD datasets, the LSTM surpasses the classifiers in this strategy. By adding more study avenues into the suggested system, this research effort can be improved in the future.

In 2020 Nayyar, et al. [7] suggested a machine learning technique based on LSTMs that uses honeypots to detect unusual network traffic patterns and routes all harmful queries to a black hole server. This technique has been tested and trained on the CICIDS2017 data set, which contains a range of attacks, including patator-based attacks. They provide a 96% reliable abnormality identification method based on LSTM neural networks for effective DDoS assault detection. The need for high-precision floating point arithmetic operations is the model's lone obvious flaw.

3. PROPOSED SYETEM

In this section, Honeypot enabled Intrusion Detection using Optimized deep Learning (HIDOL) technique has been proposed as a way to identify IoT device attacks. Initially, A honeypot server is placed to find malevolent activity in IoT devices and the patterns are gathered from the attacker. The necessary data are extracted during the feature extraction procedure using a one-hot encoder. By using the Dingo Optimization, the essential features are selected. The Conv-BiLSTM model will classify the vulnerabilities like DDoS attacks, physical attacks and Ransomware attacks. Figure 1 shows the proposed HIDOL technique.

3.1. Honeypot Server

An apparatus that logs the attacker's attack strategy is called a honeypot. It does not decrease the force of the attack or stop it. It learns about the attacker by following their movements and gives them the information they ask for. The purpose of the honeypot server is to detect malicious activity on Internet of Things devices and to collect patterns from the attacker. This technique makes use of a Cowrie honeypot to record SSH and Telnet connections. This is where the session's data is recorded. These honeypots are often connected to the Internet in order to continuously monitor the hosts, scripts, and resources that password-guessing attackers use.

3.2. Feature Extraction

In future extraction it will extract the datas from honeypot to detect the threads like DDoS, Ransomware and physical attack. In this the One-Hot Encoder tracks the

attacker's movements and then extracts the necessary features from the data.

3.2.1. One-Hot Encoder

One-hot encoding, also known as bit-effective coding. This method is applied in a machine-learning model to encode category variables into numeric values. Applying numerical data makes deep learning techniques and machine learning more accessible. In this the vector representation for every system call and a unique system call for every place. As a result, different numbers of system calls correlate with varied input vector sizes.

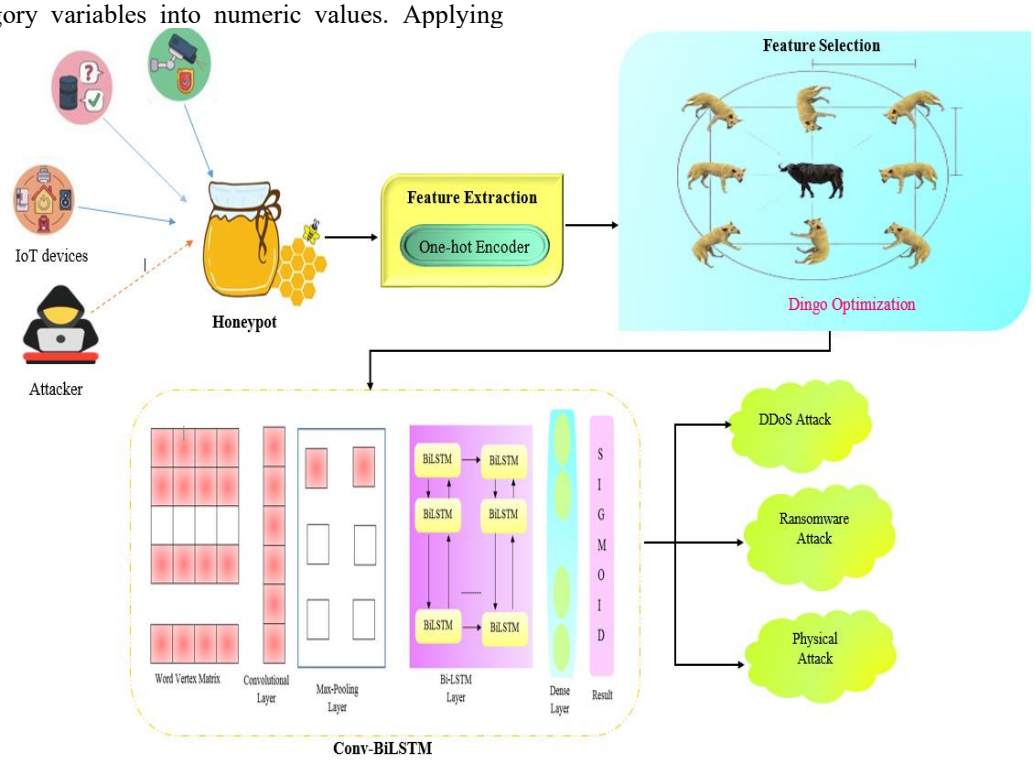

Figure 1. Workflow of the proposed HIDOL Technique.

3.3. Improved Dingo Optimization

Improved Dingo Optimization's (IDO) optimization model is made for feature selection, which optimizes data and provides pertinent features. Finding the best real-world system solutions is a difficult task. Because there are multiple excellent solutions available. The improve persecution, scavenging, group attack, and survival are shown in equation (1)-(2).

$$\propto= (BF - WF) \tag{1}$$

$$X = \frac{mean\ (X(F-WF))}{mean\ (X(F-BF))} \tag{2}$$

$$CB = \propto \times \left(\frac{P}{X}\right) \tag{3}$$

The best and worst objective functions are denoted by the terms BF and WF, respectively, in this instance. Fitness is represented by F, distance by A, generality by X and p, and arbitrarily by CB, which is a number between 0 and 1.

3.4. Conv BiLSTM Layer

The Conv-BiLSTM model is used to classify the data source assault. The framework of the proposed model is described in the following section. The five steps that comprise the Conv-BiLSTM model's higher levels structure.

3.4.1. Word Vectorization

The system eventually converts the outcome of the selecting features process into discrete words or tokens. This converts every token into the numerical representation of a vector. GloVe and Word2Vec, two pre-trained word-embedded models, are employed to create the word vector matrix. The model's accuracy is evaluated using the Word2Vec and GloVe models. The input text can be expressed by $P = \{a_1, a_2 \dots \dots \dots a_n\}$, where a_1 through a_n are word vectors with length f, and P indicates the length n.

$$P = a_1, a_2 \dots \dots \dots a_n \in R^{n*f} \tag{4}$$

Although the lengths of the input texts may vary, every output text should be the same length (l). No padding was used to lengthen its length. Text that exceeds the allowable length, l, will be chopped off. However, if the text is shorter than length (l), no more paces are added to the total. This results in a uniform matrix dimension for all texts. Any -dimensional text has the following definitions:

$$P = a_1, a_2 \dots \dots \dots a_n \in R^{i*f} \tag{5}$$

3.4.2. Convolutional Layer

The primary level of the CNN model, the convolution layer, is excellent at determining which words are most important in a phrase. The layer of one-dimensional convolution created from the word embedding step receives

the data set $P \in R^{i*f}$ of word vectors. To create the local feature of an n-gram, a convolution word vector matrix with N filters and a convolution kernel width of q is constructed in a one-dimensional convolution layer.

$$e_i^m = f(a^m \otimes X_{i:i+a-1} + T^m) \quad (6)$$

The weight matrix a represents the word vector dimension d, the convolution process, and T^m the bias of the filter F_n.

3.4.3. Max-Pooling Layer

The convolution method creates the feature maps, while the pooling layer selects the best properties, $m = \max\{m\}$, to compute the local acceptable statistics. To deliver a single output containing the maximum number. One-dimensional max-pooling is used to aggregate a down-sampled representation of the original input and its kernels. By efficiently reducing the number of features, the CNN model avoids overfitting and speeds up training while simplifying parameter tweaking.

3.4.5. BiLSTM Layer

In a departure from LSTM, Bi-LSTM employs hidden states to facilitate information flow in both directions. It might enhance the ability of Bi-LSTMs to recognize contextual cues. Using these bidirectional links, it is possible to Maintain input data that comes from the past and the future, rather than requiring decay to integrate future information as is the case with the usual RNN model. Typically, a Bi-LSTM is built by linking the outputs of two competing LSTM networks. The Bi-LSTM will proceed to weigh the results.

3.4.6. Dense Layer and Result

A dense layer in this approach uses values to connect the inputs and outputs. In the last layer, the final output is generated using a function called a sigmoid. The average generated at random is translated to binary format. Equation (7) depicts the sigmoid function's predictive performance.

$$R = Sigmoid\ (uf + q) \quad (7)$$

Binary cross-entropy can be used to classify the data as either 0 or 1 based on the sentiment analysis result. In this study, a negative perspective is represented by a score of 0 and a positive perspective by a score of 1.

4. RESULT AND DISCUSSION

4.1. Description of the dataset

KDDCUP 19 Dataset

This dataset was created using information from the 1998 DARPA IDS evaluation program and utilized in the third global Competition for Knowledge Development and Data Mining Tools. The KDD-Cup dataset contains 41 dimensions in total. There are 31279 KDD Cup instances and 33746 ISCX instances in the used subset.

4.2. Description of evaluation matrices

Throughput

Throughput is the actual bandwidth measured at that precise instant during file transmission. In contrast to bandwidth, that is generally stated in bits per second (bps), throughput more properly represents the actual bandwidth over a certain time period and under specific network conditions, particularly when downloading a specific item. It is calculated by dividing the total quantity of data (in bits) successfully conveyed by the total amount of time (in seconds) over which the data was transmitted.

$$Throughput = \frac{Total\ number\ of\ transmitted\ data}{Total\ time\ to\ trasmit\ a\ data} \quad (8)$$

Packet Loss

The percentage of frames dropped throughout data transmission is referred to as packet loss. Packet loss is an important metric to know how many packets are lost. Network collisions and congestion are the causes of this. It is computed in the following format:

$$Packet\ Loss = \frac{Amount\ of\ loss\ pocket}{Total\ number\ of\ packet\ send} \times 100 \quad (9)$$

Detection Rate

The Detection Rate (DR) is a vital measure of the system's ability to consistently identify attacks from all positive occurrences. IDPS is critical to cybersecurity, especially in terms of attack prevention. The following formula is used to obtain the detection rate:

$$Detection\ Rate = \frac{True\ Positive}{True\ Positive + False\ Positive} \quad (10)$$

Performance of Throughput

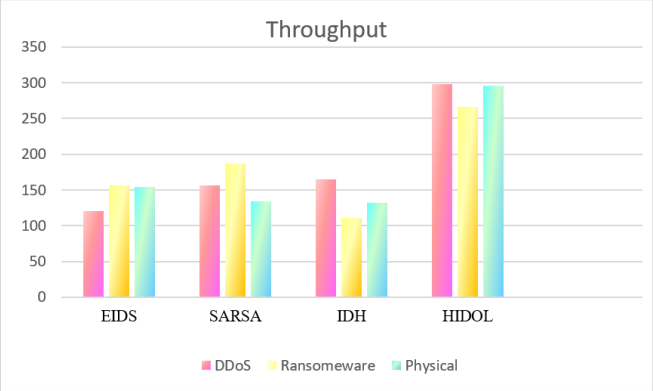

Figure 2. Throughput on Attacks

Figure 2 describes the throughput on attacks. The suggested HIDOL is contrasted with existing techniques like EIDS, SARSA, and IDH. This method archives the highest throughput value when compared to other existing techniques.

Detection Rate

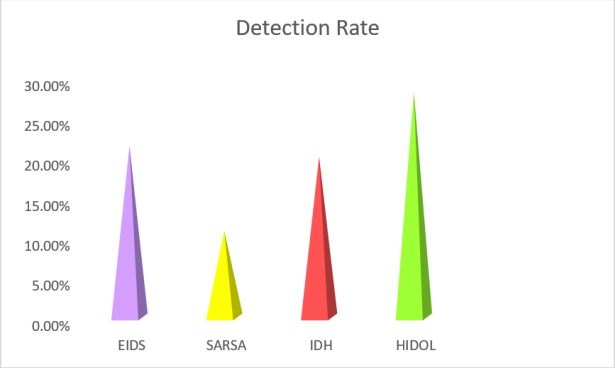

Figure 3. Comparison of Detection rate

Figure 3 illustrates the proposed and current systems' detection rates using the dataset. With a detection rate of 28.07%, the proposed HIDOL archives outperform the current system in comparison.

Time Efficiency

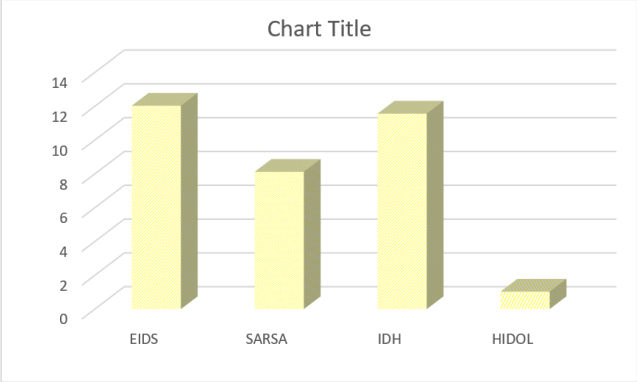

Figure 4. Quickly and effectively vulnerabilities in a system

Figure 4 displays how quickly and effectively vulnerabilities in a system or IoT devices may be found and examined is referred to as time efficiency in vulnerability detection. The proposed HIDOL systems time of 1.03 milliseconds is quick compared to EIDS, SARSA and IDH which takes 12.03, 8.12 and 11.54 respectively.

5. CONCLUSION

In this paper a Honeypot enabled Intrusion Detection using Optimized deep Learning has been suggested as a way to identify the attack in IoT devices. A honeypot server is placed to gather the patterns from the attackers. In this the necessary data are extracted during the feature extraction procedure using a one-hot encoder. By using the Dingo Optimization, the essential features are selected. The Conv-BiLSTM model will classify the vulnerabilities like DDoS attacks, physical attacks and Ransomware attacks. KDDCUP 19 datasets are employed to assess the suggested system's efficiency. The proposed system is evaluated using python programming. Evaluation measures like Throughput, Detection Rate and time efficiency have been employed to assess its effectiveness of the recommended intrusion detection method. The suggested HIDOL archives rate for identification is 28.07%, which is greater than the current system in comparison. In future this research focus on increases the performance more than this using optimization process.

CONFLICTS OF INTEREST

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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AUTHORS

Jeya S. Shemona is an Assistant Professor with 4 years of teaching experience in the field of Electronics and Communication Engineering. She earned her Ph.D. from Anna University with a specialization in Computer-Aided Diagnosis Systems for the early detection of cancer in red blood cells using image processing and deep learning techniques.
Her areas of expertise include Image Processing, Machine Learning, Pattern Recognition, Deep Learning, and Medical Image Analysis. She has published research papers in reputed journals, authored the book Computer Aided Diagnosis System for Early Detection of Cancer in Red Blood Cells, and serves as a reviewer for the Journal of Imaging Informatics in Medicine. She also holds a published patent for a solar panel cleaning robot for industrial solar power plants.
Dr. Shemona is actively involved in academic research, innovation, faculty development programs, and technical conferences. Her commitment to quality education and research excellence continues to contribute to advancements in engineering and emerging technologies.

Sree Arthi D M.E**,** is currently working as an Assistant Professor in the Department of Electronics and Communication Engineering at Sree Sakthi Engineering College, Karamadai, Tamil Nadu, since 4 June 2025. She has rich academic and industrial experience in the fields of Electronics and Communication Engineering, Automotive Embedded Systems, and Communication Networks.
Prior to joining academia, she worked as an Embedded Consultant at L&T Technology Services, Bengaluru, and as a Software Integrator at Bosch Global Software Technologies Private Limited for Audi and Porsche projects. She has expertise in automotive software integration, embedded software development, software testing, and automotive tools and technologies.
She has published one research article in an international journal and presented ten papers at national and international conferences. She is an active member of the Indian Society for Technical Education (ISTE), and the Computer Society. Her research interests include Automotive Embedded Systems, Digital Communication, Computer Networks, Wireless Communication, and Embedded System Design.
She is passionate about teaching, research, and lifelong learning and actively participates in academic, technical, and professional development activities. She is committed to mentoring students and contributing to technological innovation and excellence in engineering education.

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RESEARCH ARTICLE

CNN-MPFM: Deep Learning Based Face Recognition for Healthcare Patient Monitoring Systems

Christilda S[1,*], Ahilan A[2]

[1] Research Scholar, Department of Master of Engineering, Ponjesly College of Engineering, Tamil Nadu, 629003, India.
[2] Associate Professor, Department of Electronics and Communication, PSN College of Engineering and Technology, Tirunelveli,Tamil Nadu, 627152, India.
[*]*Corresponding e-mail: schristilda@gmail.com*

Abstract Face recognition is one of the techniques used to identify and classify individuals that has distinctive features of their face for automated healthcare monitoring. Intelligent face analysis is indispensable in the medical field for improving patient safety, rapidly assessing patient status, and live monitoring. However, many existing methods rely on conventional facial analysis or basic classifiers, which limits recognition accuracy and reduces performance under varying facial expressions and real-time conditions. To overcome these restrictions, a Convolutional Neural Network with MediaPipe Face Mesh (CNN-MPFM) model is proposed. Initially, the input patient facial images are preprocessed using face detection, resizing, and normalization. The output of the processed facial images is then passed to the MediaPipe Face Mesh module, which provides more detailed facial information with precise facial landmark coordinates and structural facial information. CNN model is an intelligent classification to determine if patient is in normal or suffocated condition, given the prominent features that were retrieved. The suggested CNN-MPFM framework is evaluated with accuracy, precision, recall, F1-score, loss and classification efficiency. The experimental analysis results show that the accuracy, precision, recall, and F1-score of the suggested CNN-MPFM method are 99.52%, 99.46%, 99.49%, and 99.47% respectively. Furthermore, the proposed CNN-MPFM approach enhances the classification accuracy over the previous deep transfer learning, ConvNet, MobileNet-V1 and multi-modal recognition approaches.

Keywords *– Deep Learning, Face Recognition, Healthcare Systems, Patient Monitoring and Convolutional Neural Network.*

1. INTRODUCTION

Face recognition in healthcare patient management systems has become essential due to the rapid growth of digital healthcare services, smart hospitals, and automated monitoring environments [1]. For successful clinical operations, these systems must be able to identify patients reliably, in a contactless manner and be constantly monitored [2]. Conventional manual identification techniques are laborious and prone to mistakes, and inefficient in handling large patient volumes [3]. Face Recognition is an effective biometric technique, which is based on the distinctiveness of facial features for identification and validation of individuals. [4]. However, traditional face recognition methods are not very effective when the lighting condition changes, posture changes, facial expressions, or partial occlusion [5]. Thus, the challenge of obtaining accurate and efficient face recognition is still a difficult one in the patient management systems in health care.

A few models based on ML and DL have been proposed to solve these problems [6]. The moderate recognition performance of conventional methods like PCA, LBP and SVM methods do not represent the complex facial representation [7]. Transfer learning-based frameworks have been shown to enhance the recognition accuracy but they tend to demand vast amounts of training data and more computational resources [8]. Facial landmark-based systems augment the analysis of facial structure but may not be as efficient when under real time monitoring conditions [9]. Likewise, CNN based face recognition models are found to have better classification capability, whereas certain models suffer from the problem of overfitting and have lesser generalization on unseen patient images [10]. Other existing work also involves complex pre-processing pipelines that result in a higher computational delay and less real time applicability [11,12].

To overcome these problems, CNN-MPFM model is proposed to address the challenges of intelligent patient monitoring in healthcare and face analysis in media pipe face mesh [13,14]. The proposed CNN-MPFM processes the input facial image by performing the processing in pre-processing phase, namely face detection, resizing and normalization, to facilitate efficient analysis [15]. Then, MediaPipe Face Mesh is used to compute accurate 2D facial landmark coordinates and facial structural features online, which reduces the computation complexity [16]. The extracted landmark features are transmitted to CNN model for effective patient condition classification based on discriminative facial patterns learned [17]. For healthcare monitoring application, the output images are classified as

normal (or suffocated) images [18]. Last but not least, the classified results can be fed to smart hospital systems for timely decision making, patient safety, and automated monitoring support [19,20]. Proposed CNN-MPFM model is more accurate in classification than existing, less time consuming in processing and more efficient in healthcare monitoring. Major contributions of CNN-MPFM method are given below.

- ♣ Primary objective of proposed CNN-MPFM method is to build an intelligent and efficient healthcare monitoring system to enhance patient condition classification by analyzing the facial image.
- ♣ The proposed CNN-MPFM approach involves using MediaPipe Face Mesh to obtain the precise facial landmark points for the accurate real-time representation of the facial features.
- ♣ The model used is a CNN that is capable of effectively identifying the discriminative facial patterns and categorizing the patient conditions into normal and suffocated classes.
- ♣ TThe proposed framework uses preprocessing method of the image like face discovery, resizing, normalization of image to get the better quality of the image and to improve the performance of classification.

The experimental results demonstrate that proposed CNN-MPFM method has a higher classification accuracy, precision, recall, and F1-score with applications in healthcare monitoring. Proposed framework is realised in Python.

Remainder paper is organized as follows: The literature survey about healthcare face recognition and patient monitoring systems are described in section 2. The suggested CNN-MPFM methodology for patient condition classification is explained in Section 3. Routine of suggested model is examined in Section 4 using several assessment measures. Finally concluded and upcoming work is discussed in Section 5.

2. LITERATURE SURVEY

Recent advancements in DL technologies have significantly upgraded face recognition and healthcare monitoring systems by enhancing feature extraction, classification accuracy, and intelligent decision-making performance. In recent years, various models have been proposed to support facial diagnosis, patient identification, disease detection, and emotion recognition in healthcare environments. Some of the recent deep learning-based healthcare face analysis approaches are summarized in this section.

In 2020 Jin, B., et al., [21] suggested performing computer-aided facial diagnosis for a variety of illnesses utilizing deep transfer learning using facial recognition. Utilize a relatively small dataset to do computer-aided face diagnosis in the trials for both single (beta-thalassemia) and multiple disorders (beta-thalassemia, hyperthyroidism, Down syndrome, and leprosy). The success of deep transfer learning applications in facial diagnosis with a limited dataset may lead to a low-cost, noninvasive approach to disease screening and detection.

In 2021 Onyema, E.M., et al., [22] described a method for recognizing facial expressions using the convolutional neural network (ConvNet), a deep learning algorithm. For training, samples of seven common face expressions were gathered from the FER2013 dataset. The proposed approach comes to the conclusion that by enhancing accuracy, visual identification, and interpretation of facial ideas and traits, deep learning-enabled systems for facial expression recognition improve the health sector's efficiency and prediction.

In 2020 Salama AbdELminaam, D., et al., [23] created a comprehensive FR system utilizing cloud and fog computing transfer learning. Deep convolutional neural networks (DCNN) are used in the developed system because to the dominating representation. According to all parameters, experimental findings demonstrate that the suggested approach outperforms alternative methods. The proposed approach outperforms the comparator algorithms in terms of accuracy (99.06%), precision (99.12%), recall (99.07%), and specificity (99.10%).

In 2021 Akter, T., et al., [24] proposed a transfer learning-based paradigm for autism face recognition to more precisely identify young children with ASD. Additionally, based only on autistic image data, our classifier identifies different ASD categories using the k-means clustering technique. The suggested method enhanced MobileNet-V1 model exhibits the best accuracy of 90.67% and the lowest value of both fall-out and miss rate of 9.33% when compared to other classifiers and pre-trained models. The improved MobileNet-V1 model showed the best accuracy (92.10%) for k = 2 autism subtypes.

In 2024 Mutawa, A.M. and Hassouneh, A., [25] suggested using machine learning, an optical flow algorithm, and electroencephalography (EEG) to develop a multimodal intelligent real-time emotion recognition system. Four-band virtual power channels—alpha (8–13 Hz), beta (13–30 Hz), gamma (30–49 Hz), and theta (4–8 Hz)—were employed with 14 EEG inputs. reached a maximum recognition rate of 87.25 % with only EEG data and 90.25 % using only face landmarks. 99.3% accuracy was attained in a multimodal approach when both the face and EEG streams were analyzed.

According to the literature review, various face recognition methods focus on conventional feature extraction and single-modal learning, which limits the ability to capture complex facial patterns under different healthcare conditions. Traditional classifiers are used in many existing models, which exhibit poor performance in case of poses, illumination variations, occlusion and facial expressions. Furthermore, several methods have poorer recognition performance and higher misclassifications in a real-time patient monitoring context. These constraints decrease the reliability and efficiency of automated health care patient management systems. To overcome these challenges, a potential solution is to combine MediaPipe Face Mesh with a deep learning model, a CNN reliably cutting facial

landmarks and recognize faces intelligently within medical contexts.

3. PROPOSAL CNN-MPFM METHODOLOGY

This section proposes a DL-based Convolutional Neural Network with MediaPipe Face Mesh (CNN-MPFM) for healthcare face recognition framework for better patient identification and monitoring in healthcare settings. The architecture includes patient image acquisition devices, patient image preprocessing modules, face landmark detection and intelligent classification to guarantee the reliable analysis of patient healthcare data. The captured facial images are transmitted to the processing unit, where image normalization and face alignment are applied, followed by MediaPipe Face Mesh based facial landmark extraction. Extracted facial features are then forwarded to CNN classification network to identify meaningful facial patterns and patient conditions. Based on the learned representations, the facial images are categorized into normal and suffocated classes. Overall workflow of developed CNN-MPFM system is shown in Figure 1.

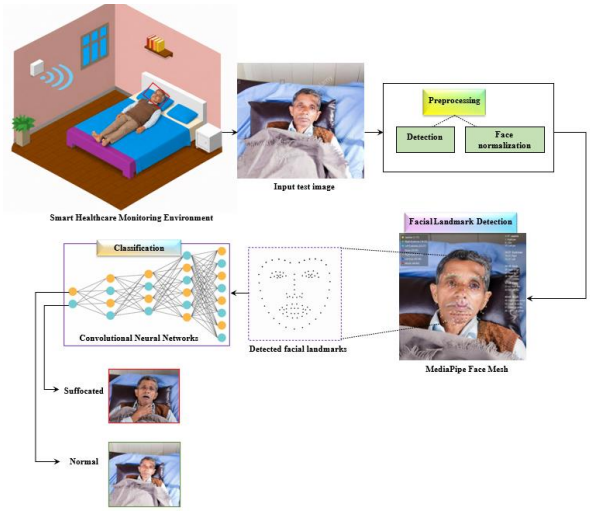

Figure 1. Overall workflow of Proposed CNN-MPFM model

3.1 Preprocessing

Input image is captured from the patient monitoring camera and used for facial feature analysis in the proposed CNN-MPFM healthcare system. The process of preprocessing is carried out to prepare the captured facial image data for analysis. This image data is organized by means of face detection and normalization to obtain uniform scaling. The process improves the quality of facial images and enhances performance of proposed healthcare monitoring model.

3.1.1. Face Normalization

The most common normalizing method which changes all the input values into a single value whose average is zero and its standard deviation is one. The SD and mean are calculated of each property. Each value of an attribute X is normalized using the calculated standard deviation and its mean. The transformation equation is the following:

$$Z = \frac{Y-\beta}{\delta} \quad (1)$$

Where β = mean of attribute Y and δ = SD of attribute Y. This method's benefit stems from its ability to lessen the impact of outliers on the data.

3.1.2. Face detection

A few basic statistical methods were used to begin machine face detection. Among them, Eigenfaces was one of the most well-liked. It represents every image as a vector of weights obtained by projecting on eigenfaces components. Even though statistical techniques are not very effective, they provide assurance that the machine can identify a human face without intervention from other sources. It has a lasting effect on future advancement.

3.2 Facial Landmark Detection

Proposed healthcare monitoring system is implemented with Python and OpenCV. The suggested approach uses Face Mesh to identify and locate face landmarks using Google's MediaPipe library. For real-time applications, MediaPipe library is effective and pre-trained. Face Mesh method uses a two-step neural network process to extract from a two-dimensional facial image the exact three-dimensional coordinates of 468 points an individual's face. BlazeFace, the first network, uses full image analysis to identify faces. In order to locate landmarks, the second network works inside the identified face region. The pipeline as a whole may operate in real time on common devices and is geared for high-speed processing. Moreover, the framework can track previous facial crops for continuous facial landmark tracking, so that the power and memory consumption and CPU usage are reduced. These facial landmarks are then extracted and used for intelligent patient condition analysis.

3.2.1 MediaPipe Face Mesh

MediaPipe Face Mesh is highly developed technique that offers an ongoing set estimated directs for key facial landmarks in real-time and identifies key facial landmarks. This technique is able to determine the 3D surface of a person without the need of a depth sensor. The Face Mesh module is based on the BlazeFace framework, which leverages the MobileNetV2 and SSD detector frameworks to optimize for mobile GPU inference. The integration of MediaPipe Face Mesh landmarks into more extensive healthcare monitoring systems is made easier by Google's computer software development kits (SDKs) and application programming interfaces (APIs). The model was developed using the TensorFlow framework, which allows users to retrain or adjust the model according to the requirements of their application. This is advantageous because it realistically represents the motion of the facial landmarks and deformation of the facial structure in real time. Using predetermined landmarks makes it easier to analyze facial regions such as the eyebrows, eyes, lips, nose, and jawline. Variations in important facial places can be utilized for intelligent patient condition monitoring and classification.

3.3 Patient Condition Classification using CNN

CNN is used for accurate patient condition categorization by learning important facial features and patterns from the

extracted face mesh data. One-dimensional (1-D) Convolutional Neural Network, a well-known deep neural network, is utilized in the proposed CNN-MPFM approach as convolution kernels only scan the logging curves' depth direction. Convolutional, pooling, and fully linked layers make up the CNN. CNN uses convolution and pooling processes to extract implicit characteristics from input data. After that, a completely linked layer receives the combined extracted characteristics. Finally, Figure 2 shows how an activation function is employed to give a neuron's output nonlinearity.

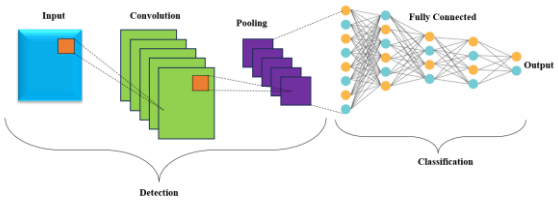

Figure 2. Basic CNN architecture

A crucial component of the CNN is the convolution layer. Each convolutional layer has several convolutional kernels that are convolved with input data in order to extract hidden features and create feature maps. The convolutional layer's output is generated by passing the feature maps through a non-linear activation function. The following is an expression for the convolutional layer:

$$d_i = r(e_i * y_i + b_i) \quad (2)$$

where y_i shows input of layer of convolution. d_i is i^{th} feature map output, e_i is a matrix of weights, * shows dot product, b_i is bias vector, and $r(\cdot)$ shows activation function. A common choice for CNN activation functions is rectified linear unit (ReLU) function. ReLU is defined mathematically as:

$$d_i = r(g_i) = max(0, g_i) \quad (3)$$

where g_i is a component of feature maps that are produced by convolutional procedures. The pooling operation's purpose is to reduce feature map size and avoid overfitting. One of the most used pooling techniques is max pooling. This is accomplished to determine the highest value of a designated area in feature maps.

$$\gamma(d_i, d_{i-1}) = max\ (d_i, d_{i-1}) \quad (4)$$

$$p_i = \gamma(d_i, d_{i-1}) + \beta_i \quad (5)$$

where $\gamma(\cdot)$ is maximum subsampling function for pooling. Bias is represented by β_i while the output of the max-pooling layer is indicated byp_i. The final output vector is then calculated by the fully linked layer after receiving feature maps produced by convolutional and pooling processes, as seen under:

$$y_i = r(t_i p_i + \delta_i) \quad (6)$$

where y_i shows concluding output path, δ_i is the bias, and t_i is a weight matrix. CNN model finds accurate classification of patient conditions into normal and suffocated classes based on extracted facial features.

4. RESULT AND DISCUSSIONS

In this section, presented CNN-MPFM method is evaluated and compared with existing frameworks. CNN-MPFM proposed method is implemented through a regular computing environment using Python based frameworks. To verify the effectiveness of the CNN-MPFM anticipated model, evaluation metrics of accuracy, precision, recall, and F1-score are hand-me-down to measure performance.

4.1. Evaluation metrics

Typical is estimated based on standard evaluation measures that include accuracy (ACY), recall (RCL), precision (PCN), and F1-score (F1S) that offer a thorough examination of intrusion detection capabilities.

$$ACY = \frac{TP+TN}{TP+TN+FP+FN} \quad (7)$$

$$PCN = \frac{TP}{TP+FP} \quad (8)$$

$$RCL = \frac{TP}{TP+FN} \quad (9)$$

$$F1S = 2(\frac{precision*recall}{precision+recall}) \quad (10)$$

Whereas FP and FN indicate false positive and negative cases, TP and TN indicate true positive and negative cases.

Table 1. Performance Analysis of Proposed CNN-MPFM Model

Classes	ACY (%)	PCN (%)	RCL (%)	F1S (%)
Normal	99.58	99.52	99.55	99.53
Suffocated	99.46	99.4	99.44	99.42
Average	99.52	99.46	99.49	99.47

Table1 shows the proposed CNN-MPFM model achieves effective patient condition classification. For the Normal class, it attains 99.58% accuracy and 99.53% F1-score. For the Suffocated class, it obtains 99.46% accuracy and 99.42% F1-score, showing reliable detection performance. The overall average results of 99.52% accuracy, 99.46% precision, 99.49% recall, and 99.47% F1-score confirm efficiency of proposed healthcare monitoring system.

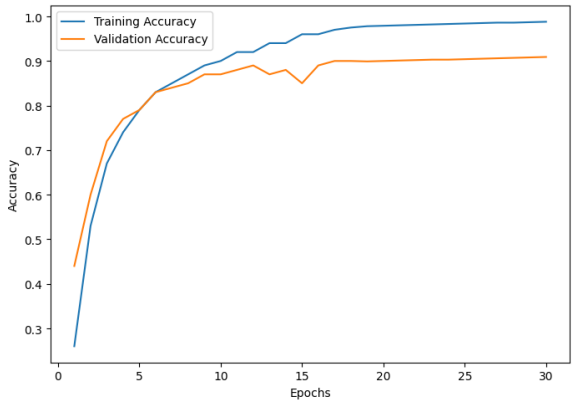

Figure. 3 Training and Validation Accuracy

Figure 3 indicates accuracy curve of proposed CNN-MPFM method. Training accuracy increases from 26% at initial epoch to 98.8% at the final epoch, demonstrating strong learning performance. Likewise, the validation accuracy improves from 44% to 90.9%, indicating good generalization ability on unseen data. The consistent improvement in training and validation accuracy confirms effectiveness of proposed method for patient condition classification.

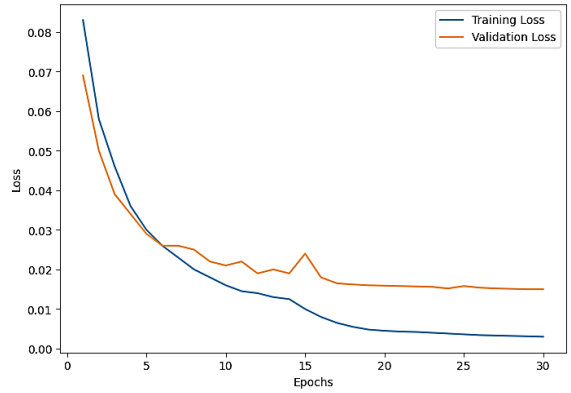

Figure. 4 Training and Validation Loss

Suggested CNN-MPFM model's loss curve over 30 training epochs is shown in Figure 4. Effective model learning is demonstrated by the training loss, which dramatically drops from 0.083 in the first epoch to 0.003 in the last. Similarly, the validation loss also drops from 0.069 to 0.015, and the amount of classification error is minimal, leading to continued convergence. The gradual reduction in the number of losses demonstrates the model's robustness and optimization potential.

Table 2. Comparative analysis of existing and proposed CNN-MPFM method

Authors	**Methods**	**Accuracy (%)**	**Precision (%)**	**Recall (%)**
Jin et al. (2020)	Deep Transfer Learning	91.25	90.84	90.96
Onyema et al. (2021)	ConvNet	93.4	92.85	93.12
Akter et al. (2021)	MobileNet-V1	92.1	91.76	91.94
Mutawa et al. (2024)	EEG + Facial Landmarks	99.3	99.12	99.18
Proposed CNN-MPFM Model	CNN-MPFM	99.52	99.46	99.49

Table 2 depicted in proposed CNN-MPFM model gets the best accuracy of 99.52%, precision of 99.46%, and recall of 99.49%.The proposed model achieves improved patient condition classification accuracy over the state-of-the-art approaches like Deep Transfer Learning, ConvNet and MobileNet-V1.These findings demonstrate how well CNN and MediaPipe Face Mesh can be integrated for intelligent healthcare monitoring applications.

CONFLICTS OF INTEREST

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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AUTHORS

Christilda S is a Bachelor of Engineering (B.E.) graduate and is currently pursuing a Master of Engineering (M.E.). She has a keen interest in Artificial Intelligence, Machine Learning, Image Processing, and Computer Vision. She is passionate about learning emerging technologies.

Ahilan A received Ph.D. from Anna University, India, and working as an Associate Professor in the Department of Electronics and Communication Engineering at PSN College of Engineering and Technology, India. His area of interest includes FPGA prototyping, Computer vision, the Internet of Things, Cloud Computing in Medical, biometrics, and automation applications. TCS, Bangalore, where he has guided many computer vision projects and Bluetooth Low Energy projects. Meanwhile, special Guest lectures, Practical workshops, Hands-on programming in MATLAB, Verilog, and python at various technical institutions around India.

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