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EVOLVING SPIKING NEURAL NETWORK: A COMPREHENSIVE SURVEY OF ITS VARIANTS AND THEIR RESULTS

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ABSTRACT

This study presents the deep insight and comprehensive analysis of evolving spiking Neural network (eSNN) development in recent years (last eight years). eSNN has been used to a vast number of optimization problems. It has several advantages: computationally inexpensive, knowledge-based, on-line learning method, and we have analyzed the improvements of eSNN in different application zones. This review paper discusses eSNN optimization done by researchers using distinct optimization techniques to achieve the possible best accuracy. In this inclusive study, few publications using eSNN have been gathered and summarized. First, we introduce eSNN. Then, we characterized the current versions of eSNN into 5 variants mainly Hybridization, Modifications, Multi-objective, Dynamic, and Integration. Afterwards, the results of the studied eSNN models being evaluated. The review paper is summed up by giving a conclusion of the optimized eSNN model's fundamentals and providing thinkable future directions that can be explored in the current works on the Hyper-parameter optimization of eSNN.

Keywords: *eSNN, Variants, Hyper-Parameters, Optimization, Comprehensive Analysis*

1. INTRODUCTION

Artificial neural networks (ANNs) are motivated by the erection and human brain purpose. They have been used as an influential computational mechanism to unravel complex function estimation, classification problems, and pattern recognition. Issues that are not sensibly amenable by other analytical mechanisms [1]. By the passage of time, ANNs have grown into more prevailing and biologically realistic models [2]. Artificial Neural Networks have converted the in-practice standard means to execute supervised, unsupervised, and reinforcement learning tasks. Their ongoing achievements reach to the level of image classification that performs human expertise for medical diagnosis. These important developments have been made through algorithmic development. Investigations of the cortical pyramidal neurons revealed discrete spikes timing as a mode of encrypting information, which is very imperative in neural networks [3]. Spiking Neural networks, termed as the third generation of artificial neural networks, have been presented in the theoretic neuroscience literature as systems of spiking neurons [3]. They are considerably close to the human brain structure due to their spiking nature (i.e. the concept of time). SNN increases the level of biological pragmatism by using individual spikes and plays a key role in biological information processing [4]. They have motivated researchers in solving problems related to optimization for classification, clustering, and prediction problems. Networks constituted of spiking neurons are competent to process a considerable number of facts using comparatively few spikes[5]. Due to their functional resemblance to human brain neurons, models based on spikes provide a powerful mechanism for evaluation of elementary processes, together with neural data processing, flexibility, and learning[6]. Like other Neural networks, SNN is also dependent on its parameter to inaugurate the best results. Spiking Neural networks are procuring admiration nowadays due to their competence in resolving various real-world problems. Conversion of real-world data should be possible by ensuring

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different directives. Such as using rate order encoding, by which amplitudes are transformed into the (instantaneous) spiking amount of neurons. The other one is time encoding, in which amplitudes are encoded into spike timings. And one more is population coding, where amplitudes are programmed into the direct shooting rate . SNN is expected to amend the performance of computers in problem fields that have been traditionally challenging for programmers. They allow integration of spatial-temporal data for communication and computation as actual neurons do. This paper focuses on evolving Spiking Neural Network, amongst the well-known architecture from the SNN family. This study aims to investigate the role of three main hyperparameters and their optimization in the learning performance of evolving spike neural networks. To inspect previously presented eSNN models, the papers from literature are selected based on the objective of this study i.e. to investigate the role of main hyperparameters in the eSNN model. And to identify the need of hyperparameter optimization in the learning of model. In the literature, there is no such published paper to date, which presents the review of optimized eSNN models. Therefore, this study provides the manifesto for further optimization of eSNN to get the best possible resulting accuracy.

The paper begins with the introduction of eSNN followed by the Algorithmic representation of eSNN. Further, the studies from literature are analyzed briefly and divided into 5 variants of eSNN namely as Hybridization, Modification, Multi-objective, Dynamic, and Integration. The Hybridization covers studies which present eSNN as a hybrid model with different algorithms. The Modification part includes studies that modified eSNN architecture to solve some real-world tasks. The multi-objective section discusses the studies which involve eSNN for multi-objective optimization. Dynamic eSNN is the variant that review studies about Dynamic eSNN. Lastly, integration discusses the studies that used eSNN to propose integrated models. The third section comprises of results and discussions from literature studies. In the end, we present the Conclusion of this review analysis based on our knowledge.

1.1 evolving Spiking Neural Network

Amongst several other SNN models, one of the popular models is called as evolving Spiking Neural Network (eSNN). Built on the ECOS methodology, an evolving spiking neural network(eSNN) was proposed in[7] which was originally designed as a visual pattern recognition scheme. The first eSNN was founded on Thorpe's neural model [8]. eSNN can learn fast and it studies a new pattern that comes from the incoming data in one pass-mode that will form a new network without retraining. eSNN is widely applied to solve classification issue [9], prediction problem [10] and pattern recognition[11]. To organize real-valued facts, each data model i.e. vectors of real-valued elements is plotted into a sequence of spikes using a convinced neural encoding procedure[12]. It enhances the importance of the direction in which input spikes reach, so making the eSNN appropriate for a variety of applications. eSNN is a one- pass, on-line learning technique, where new data is learned incrementally, including the merging/aggregating production neurons. As eSNN is knowledge-based, data is denoted as prototypes through output neurons (once they are done with aggregation) [13]. It is useful for data processing, but the problem arises is in deciding the optimum parameter values for a dataset. For every neural network, there are parameters involved and some approaches are employed for parameter setting such as manual tuning or an automated process using an optimizer. Thus, eSNN also requires an optimizer algorithm that helps in selecting optimal parameter values. According to literature insight, eSNN has three core parameters (i.e.: modulation factor (Mod), threshold factor (C), and similarity value (Sim)) which are required to be optimized before network training. These parameters have a substantial role in the accurate training of the network. The eSNN model spread on the ECOS principles to process spike-time data[13]. It can learn fast from huge data, For example, one pass learning technique from already known little knowledge. It adapts in a simultaneous environment and in an online manner where new facts based on local learning can be accommodated. It has "Open" i.e., evolving erection, where task-related incoming variables, a new association, new outputs Classes, and neurons are enumerating. Together, data learning and knowledge depiction are facilitated in a complete and flexible mode. For example: supervised and unsupervised learning, evolving bunching, "sleep" knowledge, fuzzy regulation insertion, pruning, and abstraction. They perform active communication with other systems and with the surrounding in a multimodal fashion. Representation is entertained in space and time methods i.e. both in their dissimilar scales. eSNN is a self-evolutionary in terms of success, behavior, connected knowledge representation, and global fault tolerance. The eSNN shows numerous benefits when compared with machine learning methods

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(both supervised or unsupervised) and classification models. For example, it is computationally reasonable because the computation takes place with pulses, distinction filters, and orientation discriminating cells[7]. This makes eSNN capable of online learning and premature prediction of temporal proceedings. It enhances the significance of arriving spikes order, therefore eSNN can be employed for various applications. It is an operational method with one-pass learning, which learned new data incrementally in a "life-long" learning system. Besides, it is knowledge-based therefore, production neurons represent prototypes in the cluster centers. [13]. Figure 2 illustrates the number of studies that fall in each variant category and Figure 3 illustrates the number of publications in the last few years, related to the objective of this study.

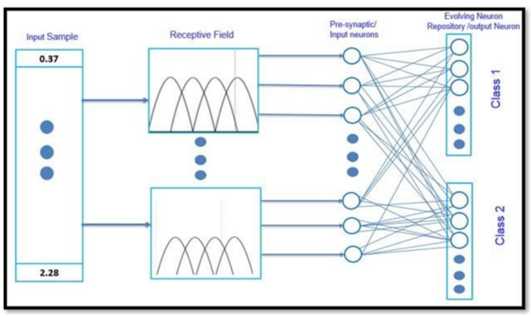

Fig. 1: Architecture of eSNN (evolving Spiking Neural Network)

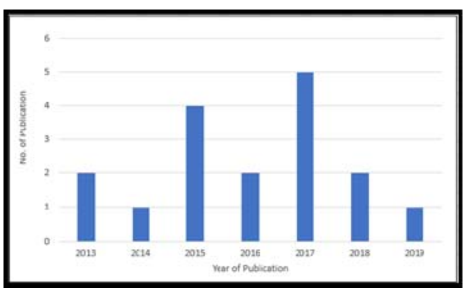

Fig. 2: Number of eSNN Publications Related To This Study

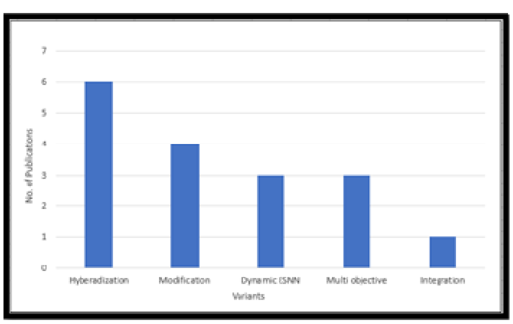

Fig. 3: Variants of eSNN

1.2 eSNN Training Steps

Algorithm 1: eSNN Training Algorithm

Require : m_l, s_l, c_l for a class label $l \in L$
1. initialize neuron repository R_l = {}
2. for all samples $X^{(i)}$ belonging to class l do
3. $w_j^{(i)} \leftarrow (m_l)^{order(j)}, \forall j \mid$ j pre-synapti neuron of i
4. $u_{max}^{(i)} \leftarrow \sum_j w_j^{(i)} (m_l)^{order(j)}$
5. $\theta^{(i)} \leftarrow c_l u_{max}^{(i)}$
6. if min (d ($w^{(i)}, w^{(k)}$)) $< s_l$, $w^{(k)} \in R_l$ then
7. $w^{(k)} \leftarrow$ merge $w^{(i)}$ and $w^{(k)}$
8. $\theta^{(k)} \leftarrow$ merge $\theta^{(i)}$ and $\theta^{(k)}$
9. else
10. $R_l \leftarrow R_l \cup \{w^{(i)}\}$
11. end if
12. end for

The detailed procedure is defined in Algorithm[13]. For every sample to be trained with class marker i ∈(i) L i.e., a new output neuron is formed. And entirely connected to the preceding neurons layer consequential to the weight vector w, with $wj \in$ R representing connections amongst presynaptic i i neuron j and previously created neuron i. In the later step, input spikes are broadcasted through the system, and the value of weight wj is calculated according to the sequence of spike transmission over a synapse j, cf. Parameter modulation factor ml is from Thorpe neural model. Function $orderj$denotes the spike rank discharged from neuron j. Here, firing threshold vi of neuron i is defined as the fraction ci ∈ R, 0 < ci <1, of the greatest feasible potential $umaxi$, cf. The fraction ci as a model constraint for each class. The weight of competent neuron is equated to neurons which are already present in the repository, cf. Now if the current neuron is smaller than the stated similarity value s, so neurons are considered as "similar". Therefore, the weight vectors and firing thresholds are combined. Once the integration is completed, the trained neuron i is cast off, and the next sample gets treated. If none of the neurons in the repository is found similar to the learned neuron i, then it is added to the repository as a new productive neuron[12].

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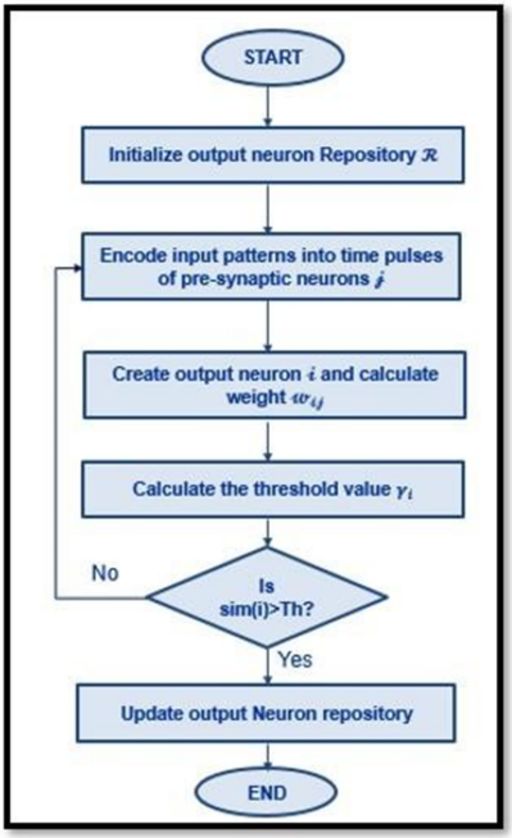

Fig. 4: Flow Chart of evolving Spiking Neural Network

Learning of eSNN is comprised of four sequential steps.

1.First, the propagate single sample from class K, into the first and second layer.

2.Then create a neuron at layer three for sample propagated at preceding layers. And weight training at this step is done using the equation:

$$\Delta W_{ij} = mod^{order(aj)}$$

Here wj, i represents the synaptic weight of the connection between second layer neuron j and third layer neuron i, modulation factor is represented as a mod that should range between 0 and 1.And order of spike arrival from j to i neuron is denoted as order(aj). At this point, the threshold of postsynaptic potential for the sample is calculated as cε[0,1], which denotes the maximum of PSP of created neurons.

3.Now the similarity factor is calculated between the newly created neurons and the neurons that are already presented in the respective class.

$$W = \frac{W_j + N_{samples} W_i}{1 + N_{samples}}$$

To calculate similarity inverse of Euclidean Distance(between connection weights of neurons) is used.

4.At this last step, the newly created neuron joins any of the class based on calculated similarity value(if it is greater than the selected threshold value), this merging of the neuron to output repository is conducted using the equation:

Here W represents the sum of all the weights of created neurons. N samples represents the total number of samples that were used to train the created Huron at layer three. At this stage postsynaptic potential needs to be updated by the equation:

$$PSP_{threshold} = \frac{PSP_j + N_{samples} PSP_i}{1 + N_{samples}}$$

2. VARIANTS OF ESNN

Below flow chart is the summary of models presented by studies that are reviewed in this study and categorized into 5 variants.

2.1. Integration of eSNN

Model eSNN-FA has been presented in [14]. They integrated eSNN with a Nature-inspired meta-heuristic algorithm named as Firefly, for parameter optimization of the eSNN model. Since eSNN lacks the ability to automatically select the optimum parameters, the Firefly Algorithm (FA) is used to determine the optimum value of eSNN parameter which are a mod factor, sim factor, and C factor (threshold). FA (Firefly Algorithm) was inspired by how the ashes' behavior of fireflies. In the proposed methodology, the parameters of eSNN are optimized using FA to get optimal performance. The integration of eSNN-FA is conducted using the well-known Wrapper method. The wrapper method takes the classifier and melds with an optimization algorithm. Then, a set of random values is used to initialize all the candidates. Subsequently, the candidates interact with each other founded on classification precision. As an example, all contributing samples will be programmed into spikes and pass over the eSNN model to discover the current suitability. The FA-Best is assigned

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with the best classification accuracy hold by the candidates. If the FA candidates encounter a better result compared to the FA-Best, the newly created FA-Best will replace the FA-Best. The iteration will be repeated until the termination criterion is reached.

2.2 Multi-objective Optimization of eSNN

MOO is the concept which enhances the process of optimization. The progression of systematically adjusting objectives at a similar time is acknowledged as vector optimization or MOO (multi-objective optimization)[15]. According to [16], the ideal solutions for multiple objectives through discrete optimization could not lead towards feasible results. Synchronized optimization is the need for various real-life optimization problems with two or more objective functions.
In [17] the scholars try to unravel multi-objective optimization for clustering problems. They aim to find a cluster based on the high similarity of substances inside an individual cluster, while the resemblance of substances from dissimilar clusters is low by using an ML algorithm named ask-means to improve eSNN learning. k-means is used when data is unlabeled. This study presented MO-keSNN (multi-objective k-means evolving spiking neural network) paradigm founded on D.E(differential evolution). In this hybrid process, k-means improve eSNN knowledge founded on multi-objective D.E by categorizing given information through a certain number of bunches (k clusters). Three main parameters that influence the segregation outcome of eSNN are optimized in this work and are known as the Mod(modulation factor), C(threshold), and Sim(similarity factor). The proposed model lifts the adaptability of eSNN in giving a better solution that can be used to conquer k-means disadvantages.
Based on MOO optimization [18] tried to answer real-world optimization issues that include numerous inconsistent objectives. Instead of a single optimization, they used MOO Optimization i.e. Multi-Objective Optimization as a solution to these real-world contradictory object optimization problems. They proposed a method to find optimal values for multiple objectives with good accuracy. eSNN was used for this purpose. To progress eSNN performance for classification problems, Differential Evaluation Algorithm was applied. Thorpe's model for eSNN was used by the researchers in this paper. The MODE-eSNN scheme was presented in this paper to discover the ideal quantity of presynaptic neurons and network parameters by treating the issue as a MOO problem. In presented MODE- eSNN, pre-synaptic neurons of the network are represented as candidates. MOO and DE were merged to conduct coupling selection criteria and fitness evaluation. It started by gathering, regularizing, and understanding the dataset. The maximum number of repetitions was then established, and the candidate size was computed. The population of the hybrid system was then produced and initialized. Each candidate value was projected for every iteration based on the DE algorithm. The process terminates once maximum iterations are grasped. The parameters of eSNN are optimized in this method to produce better accuracy of proposed hybrid MODE-eSNN.
In [19] researchers attempt to progress the performance of multi-objective optimization with eSNN. To achieve this goal, HS (Harmony Search) and memetic approach were applied. In order to advance eSNN structure and its accuracy, MEHSMODE-eSNN (Memetic Harmony Search Multi-objective Differential Evolution with evolving spiking neural network) was constructed. After that, MA(memetic algorithm) was created by [20]. This algorithm was inspired by natural progression philosophies by Darwin and Dawkins a meme notion. MA is a discrete learning method and considered as a population-based integrated GA. This paper deals with an enhanced multi- objective technique with memetic practice to attain modest and accurate eSNN.

2.3 Hybridization in eSNN

A hybridized model of eSNN has been presented in [21], where the researchers hybridized eSNN with one of the Evolutionary Algorithm named as Differential Evaluation. They attempted to solve the issue related to the optimal selection of pre-synaptic neurons for given datasets using EA. The benefit of applying EAs is its capacity to adjust to a changing domain. Pre-synaptic neurons estimation should be done before eSNN training begins. Therefore, it was the key mission in this study. Because the smaller number of pre-synaptic neurons creates few input spikes which ultimately affect learning precision, the higher number increases the computational period. The author of the paper claimed that based on literature DE has not used up till now for eSNN to optimize pre- synaptic neurons. Numerous significant parameters can regulate the result of eSNN learning. According to the author, the values of the Modulation factor, the threshold parameter, and similarity (Sim) should be in the range of 0 and 1. All information will be customized into spikes and go through eSNN to

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discover network capabilities. The integrated structure of eSNN and DE was proposed for pre-synaptic parameter optimization that is related to the accuracy of the eSNN model. This procedure of searching the finest pre-synaptic neurons has been directed by updating DE candidates until maximum iterations are reached.

Differential hybridization of eSNN was conducted in[22], a hybridized model of eSNN and Differential Evaluation algorithm for parameter tuning of eSNN are presented. They termed this model as DEPT-eSNN. The determination behind this work is to answer the problem associated with manual alteration of eSNN parameters because the optimal parameters merging leads in the direction of improved classification accuracy. DE is amongst the most influential tools of universal optimization in evolutionary algorithms (EAs) and has numerous benefits. The benefits belong to DE are its simplicity, its capability to adapt itself to a changing environment, and its efficiency as a worldwide numerical heuristic optimization technique [23]. Hence, the aim of this study was to determine optimal parameter values by enhancing eSNN learning through DE. They can be used to acquire approximated explanations for real-world problems having objective functions. Those problems are non-differentiable, noisy, stochastic, noncontinuous, nonlinear, or with local minima.

In [24] researchers proposed an integrated evolving Spiking neural Network to seek optimal eSNN parameter values for selected data sets. The main three parameters are proportion factor, modulation factor, and similarity values were optimized in this work using an optimizer. The ideal estimations of parametric values are selected by HSA (Harmony Search Algorithm), so they get suitable values for certain issues through some trial-and-error approach. The methodology for the learning of eSNN-HSA designed comprises three phases such as preparation of data, data normalization, and learning phase. In the preparation phase, five standard benchmark data from machine learning were retrieved. In the next phase for training and testing, datasets were normalized into the range [0, 1]. Then, once the data set was normalized, the eSNN-HSA trained on the data to be categorized into classes.

Clustering is amongst important unsupervised learning techniques in Data Mining. A fusion of differential evolution with k-means evolving spiking neural network (k-DeSNN) for clustering problems was proposed in [25]. The proposed approach improves the versatility of the eSNN algorithm in creating improved solutions that can be used to overcome the disadvantages of the k-means algorithm. In this study, D.E was applied to improve the learning of k-means eSNN using a specific data set categorizing a specific cluster value (k clusters). In this condition, the eSNN model based on D.E was analyzed as a clustering technique to associate the stability of both approaches to remove disadvantages. Therefore, the aims of the study are to discover such clusters with greater object similarity within separate clusters and low objects similarity from other clusters by improving eSNN learning using k-means based on differential evolution.

An innovative hybrid NHS-eSNN (harmony search algorithm with the evolving spiking neural network) for classification tasks was introduced in [26]. Harmony search was applied to advance the typical eSNN model. The researchers stated that based on the literature eSNN has some limitations, such as finding the optimal number of pre-synaptic neurons for a specified data set. This is primarily the critical one. More pre-synaptic neurons expand the computational time whereas fewer of the number of pre-synaptic neurons affect the precision of learning. Electing an optimization method to perform this parameter variation is significant. Among the numerous optimization techniques, the harmony search algorithm is used in this work. They purposed a new method to obtain a precise and simple eSNN. The new algorithm seeks for the optimal values to accomplish better accuracy and better structure of eSNN, ultimately to enhance performance for classification issues.

A network-based Intrusion Detection Systems (IDS) was proposed in [27], to observe and examine the incidents in web data flow and to pinpoint indications for possible integrity violation and intrusion attack. The researchers attempt to create an online system, which consumes the least computational power to examine basic network characteristics so that the existence and type of possible network irregularity can be detected. Therefore, to solve the problem of network anomalies, they proposed HMLADS (Hybrid Machine Learning Anomaly Detection System), which employs classification performed by eSNN (evolving spiking neural networks), to achieve proper labeled Potential Anomaly(PAN). The proposed model was built on Thorpe's model which strengthens the status of the spikes taking place in a prior moment, whereas the neural plasticity was used to observe the learning algorithm by using one-pass learning. To categorize real-valued datasets, each data model was mapped into the

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order of spikes through ROPE (Rank Order Population Encoding). Advance eSNN is organized in more than a few layers, its topology is firmly feed-forward, and the weight modification developed on the connections between neurons of multiple layers.

2.4 Dynamic eSNN

A fully connected neural network was proposed in [11]. They stab to produce a thoroughly connected and dynamically adaptive neural network classification algorithm for pattern recognition. The study presents a novel RBF-like fast dynamically mature classifier known as ESNC (evolving spiking neural classifier). The researchers claimed that based on a literature study, SNNs used by previous studies have a fixed paradigm. It means that at hidden and output layers, neurons should be specified before training started. Also, they are appropriate for classification function where classes were known beforehand because they performed batch training. However, to develop effective SNNs algorithms that incorporate with a continuously varying environment was a challenge. In later studies, the input and hidden layers were made dynamic, but the output layer remains a fixed structure. Therefore, they proposed SNN architecture with three layers of a fully connected network. Where the number of neurons in the output layer was flexible so they used a supervised learning technique to determine whether the addition of a new output neuron would be required during the learning phase.

A new model called deSNN was introducing in [28]that employs SDSP spike-time and rank-order learning in a semi-supervised, supervised, or unsupervised manners. The SDSP learning was applied to a dynamically evolving network with fluctuating connection weights that record spike data Spatio-temporal in groups throughout the training and recall process. Online learning and recognition of SST data (spatio and spectro-temporal) were provoking tasks. And it is significant for the development of independent machine learning methods. According to the authors, eSNN should mainly be used for fast speech and image recognition. Another spike learning approach, such as STDP (Spike-Timing Dependent Plasticity) and its enhanced version, SDSP(Spike Driven Synaptic Plasticity) can be applied to understand spatiotemporal depictions, but they typically require several iterations in an unsupervised or semi-supervised learning mode. Hence, there is a need for dynamic eSNN, that exploits rank-order learning and dynamic synapses to acquire SSTD in an online manner. Therefore, in the proposed deSNN, RO and SDSP learning both were employed. Though the RO learning will establish the basic values of connection weights and the SDSP rule will alter those connection weights considering further approaching spikes. Altering synaptic weights were implemented in the dynamic synapse model. Once a synaptic weight initialized, the synapse changed to dynamic and corrects its weight using the SDSP algorithm. Those dynamic synapses modify their values in parallel through the presentation of input data that was observed by the output neuron.

A new method based on NeuCube architecture for traffic forecasting with spatiotemporal data was presented in [29]. Its neural presentation allows for a visual examination of connectivity between different locations, and also offers a prediction tool connecting the predictive learning competencies of dynamic evolving Spiking Neural Networks (deSNNs). By taking benefit of the NeuCube characteristics, this work emphases on the potential of spatially alert traffic inconstant forecasts, similarly the exploration of the Spatio-temporal associations in between different sensor positions within a traffic network. By plotting the data features into the SNN model, the study aims to analyze the spatial connection of traffic generation. Research work was created on real traffic network observations attained from the Madrid Open Data Portal. Data have been taken in 51 locations of the business focus of the city from the initial six months of 2017. Traffic flow noticed in one of the locations will be applied for the target variable, while the traffic at other locations will be used as input data. Hence, the established model will let the traffic prediction at a certain location with data available from other locations, depending on their Spatio-temporal relationships. The NeuCube platform let the Spatio-temporal prediction to be conducted by encoding brain signals as data environments. Traffic sensors have been plotted to a two-dimensional network. Each traffic device was associated with an incoming neuron, a point in the network plotted to the coordinates of the sensor. This permits the conceivable Spatio-temporal connection between the areas of the traffic sensors and the scheduling of the information.

2.5 Modification of eSNN

In [30]combination of eSNN with a QAE (Quantum inspired evolutionary algorithm) has been presented to inspect eSNN potential when it is used for the

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problem of FSS (Feature Subset Selection) utilizing some wrapper approaches. The attention of the study was primarily on the weight, parameter, and feature optimization of eSNN. The purpose of this work was to explain the use of Evolutionary algorithms on how it is useful for eSNN learning and to propose PSO (Particle Swarm Optimization) based sharp algorithm, shared with Quantum principles for eSNN concurrent parameters and features optimization. QPSO is presented as a novel optimizer for eSNN. Using the well-known wrapper approach QPSO interrelates with an induction technique (the eSNN). Optimization of eSNN parameters (threshold factor (C) and neuron similarity (sim) and modulation factor (mod)) were conducted. And finally defining relevant attributes. All particles have an irregular arrangement of dual qualities and cooperate based on the accuracy of the classification. Since there are two segments to be optimized, each partition will be divided into two sections. The initial segment is used for feature optimization whereas the next part holds paired strings for parameter optimization. The data held by each particle was in the paired demonstration, therefore it is necessary to convert it into real value. Gray code strategy was chosen for this assignment as it proved to be a basic and powerful route to represent a real value from the binary presentation.

For Cyber fraud detection, eSNN has been used by [10] which utilized ESSN with slight modification for the detection of phishing websites. These are the websites where the attacker generates a copy of the website and attempts to make it a genuine website. To steal user private data. By taking advantage of the sequential learning quality of eSNN, this study tried to solve the problem of catching duplicate websites. It was built On the Thorpe's model, where the early spikes have given more importance to the visual pattern recognition system. This strategy needs to deal with real-valued information so that every data sample is required to plot with a sequence of spikes utilizing an exact neural encoding system. ROC encoding was applied in this situation. Once the spikes are created, the network must create the output neuron by relying upon the input sample and initiate the synaptic association between the input and output neurons before instating the synaptic weight. As it is a sequential learning framework, therefore it begins with zero output neurons. In the introduced network, there are three measures which are, An expansion of output neuron. To make the new neurons and to organize the connections between the input and output neurons. Conflict resolution methods such as if any wrong classifications occur, to deal with this circumstance. The closest neuron of a similar class goes into LTP(long term potentiation) and the nearest output neuron of the distinctive class synaptic weight experiences in LTD(Long Term Depression). Synaptic weight update approach for example if the new example contains knowledge that was already held by the network, at that point synaptic weight experiences in LTP [10].

An effort has been done in [31] to develop an algorithm that works in versatile and dynamic circumstances. An algorithm that gains from new examples (online learning), yet in addition to new and hidden knowledge. Therefore, they present the expression evolving learning (EL) means learning from new knowledge and without retraining models like traditional ML methods. To achieve EL's goal, two brains are involved in a deeply versatile, supervised learning algorithm data handling such as divide and conquer. And hierarchical abstraction was presented in this study. The proposed model did not enforce any restriction Data on the number of classes or methods used to feed data on the model. The presented model was based on these steps, first to enable EL participants to learn from data, its phrase "divide and rule" was used. They rely on an adapted neural model of SNN to create ECoS learners. They then practice the ordered abstraction to develop the final general framework of learning swarm. They used the optimized form of Thorpe's model for the Neural model. As computationally, it is less challenging than other biologically classy models. Thorpe's model uses order spike instead of timing spikes to encrypt the concept of time. The parameter m was the modulation parameter and determines the amount of weight reduction as the reason for the attempt of the incoming spikes from the pre-synaptic firing associations. The Thorpe method works well until the number of presynaptic connections was small. Numerical stability is degraded, however, as the number of such connection's increases. Thorpe's model requires an m-hyperparameter. To avoid hyperparameter-related problems, a parameter-free neural model was proposed to be numerically stable as the Naive Ranking Order (NRO) model.

eSNN is modified to use in the traffic domain in [32]. Implementation of an improved strategy for the acquisition of traffic patterns for any area and date that can be used by ATIS and ATMS was performed in this study. The proposed innovative methods that give long-term predictions composed by grouping based on the similarity of daily traffic data. It was achieved by using eSNN with change detection and reworking mechanism. The authors claim that there is no other work in the writing regarding the issue of long-term forecasting. The requirement for adjusting the delivered estimation along time. The presented model consisted of two phases, an off-line learning phase, where clusters are obtained using DBSCAN(density-based spatial clustering of applications with noise) and then these clusters are later fed to an eSNN classifier. Then utilized in the on-line learning stage. The classifier allocates a pattern to a day. Then, variation recognition and adaptation procedure take place. It allows us to reallocate the day to another design if it was originally inappropriate. The authors claim that the proposed structure can process some other information source with no loss of sweeping statement. As mentioned earlier, obtained clusters from the first phase are fed into the eSNN classifier. Then, before entering to on-line learning phase the eSNN at first trained with the dataset in light of historical perceptions. To get the ideal values for the primary eSNN parameters such as the similarity sim, threshold C, modulation factor m, and the number of Gaussian respective fields G. The classifier was gone through parameter tuning. Therefore, a genetic algorithm was used for parametric setup space for each area under investigation. At that point, the prepared system will be utilized for the online phase. A classification and pattern clustering scheme have been demonstrated to include a useful tool for long-term predictions. The basic concept of this strategy was crucial, and its variables were critical. were improved and the characteristics utilized are deliberately selected, it can give precise forecasts. The presented adaptation procedure distinguished the anomaly but could not give another closer pattern if this series of events were anticipated. During the clustering phase, there would also be a cluster with those same kinds of days accessible for the forecasting phase.

3. RESULTS AND DISCUSSION

In this section, we have presented the results of all the analyzed papers. We represented the result's table and discussed them based on the evaluation metric. Here we divide papers into two categories based on the evaluation metric used by the study. This section is further divided into 5 sections based on the variants as categorized previously. Each section discusses the results from the studies which are already mentioned in the previous section.

3.1. Evaluation Metric(Part 1): Classification Accuracy

Here, the performance accuracy of different eSNN models from all 4 variants is discussed. This section particularly describes the results of models tested on datasets from the UCI Machine Learning Repository (see Table 2).

3.1.1. Integration of eSNN

The results of the experiment in [14] conducted on the eSNN FA integrated model show that FA has a better adaptive ability and generalization performance [33]. These reflect the FA searching algorithm which improved the classification accuracy with eSNN. According to an eSNN-FA framework, eSNN gives better accuracy for Iris and Breast Cancer (i.e. 84% and 92% respectively) but it does not provide better enough accuracy for Wine, Heart, and Diabetics datasets (68%,78%, and 78% respectively). When comparing with standard eSNN, the classification accuracy in the testing phase is improved in all the datasets except iris where Classification accuracy is 84% which less than standard eSNN with 89.33%.

3.1.2. Multi-objective Optimization of eSNN

The process of the model presented in [17] begins with the initialization of eSNN parameter values by selecting its presynaptic neuron values based on DE. The necessary point here is to introduce the number Of k points where they pertain to the clustering process. k is assigned to two groups in this inquiry. From that point forward, the eSNN model operation will run until the desired output spikes have been achieved. When the PSP (postsynaptic potential) exceeds the threshold limit, it will fire and the changes to be made incapacitated. Finally, repeating the task of recalculating the k centroids positions and the spikes positions concerning them until the final criteria have been met. The proposed technique is assessed by utilizing a few standard datasets. According to the results, it can be viewed that MOO-keSNN provides good accuracy on the Wine dataset only but for rest three datasets the accuracy measures below 80%. But when comparing to k-means, MOO-keSNN gives better accuracy results on all 4 datasets which indicate the improvement in k-means algorithm performance. Hence, it can be concluded that optimized eSNN when using Different Evaluation techniques can overcome the limitations of k-means clustering Algorithms to

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some extent but cannot give 90% accuracy for all the data types. Hence, it can be concluded that optimized eSNN when using Different Evaluation techniques can overcome the limitations of k-means clustering Algorithms to some extent but cannot give 90% accuracy for all the data types.

The model MODE-eSNN presented in the study[18] begins by gathering, perusing, and normalizing the dataset. The highest iteration value was set, and the size of the candidate was calculated. Furthermore, the presynaptic neurons and parameters of eSNN are resolved randomly. Generation and Initialization of the population for the hybrid process was done. Each candidate was evaluated for every cycle dependent on the D.E algorithm. The proposed technique stops once maximum iterations reached. Three important parameters mod, sim, and c(threshold factor) are optimized in and the results show that finding optimum value for the combination of these parameters is difficult because of the dataset nature. This unmistakable impact was because of the connection between classification accuracy and model's parameter optimization as integrated by utilizing the familiar Wrapper approach. The results illustrate that the proposed model MODE-eSNN was capable of classifying data set with preferably good accuracy of more than 70 % for Appendicitis, Haberman, Ionosphere, and Iris but for the rest of three datasets (i.e, Heart, Hepatitis and Liver) the classification accuracy is nearly 50%.

The algorithm proposed in [19] concurrently controls the eSNN structure (pre-synaptic neurons) and its relating model parameters by handling this issue as a multi-objective optimization problem. The pre-synaptic neuron was presented as a candidate. HS and MOO are consolidated to complete a fitness assessment and mating selection strategy. In the training, the process collects the datasets and then normalized them. Then, iterations were set at the maximum number and the size of the candidate was computed. Moreover, the presynaptic neurons and parameters of eSNN were decoded. The population of the hybrid method was generated and initialized. Each candidate was then tested. Once the training ends the presented model was tested on benchmark datasets. The performance accuracy analysis was conducted for 10 folds cross-validation. From the results, it can be viewed the best-achieved accuracy is for the Iris dataset. For Appendicitis and Haberman, the accuracy is acceptable i.e., more than 70%. But for the Heart, Hepatitis, Liver, and Ionospheres, the performance accuracy is below 70%. It can be noticed that the essence of datasets has a major effect in deciding the quantity of pre-synaptic neurons for each model. Plus, the role of the algorithm is crucial in choosing correct pre-synaptic neurons for accomplishing the best execution.

3.1.3. Result: Hybridization in eSNN

The proposed hybridized model in[21], starts when vector values of all candidates were initialized with some random value. Then, for every iteration, the vector values for every candidate will be updated by just adding the value obtained by calculating the difference of two vectors to the third, then merging the new candidate's vector to the target vector to calculate the trial vector. If the new vector is superior, then the trial vector. Replace the target vector with a trial vector. This updating process should be conducted in every iteration until stopping criteria encountered. The training process will be conducted until acceptable fitness will be obtained from the best candidate vector value. Later, an experiment was performed on benchmark datasets. The reported results demonstrate that accuracy of the proposed model in the testing phase shows better performance for Iris and Breast cancer. But for Hepatitis, Heart, and Ionosphere, the accuracy of DE-eSNN was not convincing with values below 80%. According to the result, DE-eSNN is competent to classify data with better accuracy for a few datasets.

The model DEPT-eSNN from the study [22] represented as DE interrelates with eSNN to enhance the eSNN parameters (mod, sim, and threshold) values. These were measured as a candidate vector values. Every input sample will be encoded into spikes and passed through the eSNN model to find the existing fitness. This method of searching the best parameter values has been practiced by updating DE candidates until the maximum number of iterations reached. The process starts by assigning random values to the population and all candidate vector. Subsequently in each cycle all candidate vector was refreshed dependent on added weight distinction of two vectors to a third. Then the trial vector is calculated by mixing the new candidate vector to the target vector. Lastly, the target vector was swapped with a computed trial vector. This procedure repeats throughout all the iterations until stopping criteria are achieved. The learning process proceeds until acceptable fitness is achieved. Numerous significant parameters can control the consequence of learning in eSNN. The estimation of Modulation factor (mod), the threshold parameter, and neuron similarity(sim) must be somewhere in the range of

0 and 1. The model was tested on 7 benchmarking datasets namely (Haberman, Iris, Appendicitis, Ionosphere, Heart, Liver, and Hepatitis). The mean of testing phase classification accuracy of the model is good for iris i.e. 89 % and for appendicitis, it's 72%. However, for the rest of the 5 datasets, the classification accuracy is below 70%. The accuracy of DEPT-eSNN was not powerful for Liver datasets with values of 44, so it can be concluded that not all classifiers are suitable for all datasets.

The integrated structure between eSNN and HSA[24], influences the precision of the eSNN model when the HSA advances the three important parameters of eSNN. All candidates were introduced with some random values and subsequently act together dependent on the classification accuracy. By improving the HSA competitors until the maximum iterations are accomplished, it continues searching for the best parameter. The consequences of learning in eSNN are constrained by three critical parameters namely mod, sim, and c. Their values should be in between 0 and 1. Based on the outcomes the accuracy shows better execution for datasets Iris and Heart. Result values demonstrate that eSNN-HSA delivered better combination in comparison with standard eSNN. However, for Breast cancer datasets the proposed model accuracy is only 1% less than standard eSNN standard. Although it shows better performance for Prima Indians and wine, it is not enough. Besides, this evaluation shows that a dissimilar sort of datasets needs dissimilar parameters to get the ideal accuracy.

The model of the study [25] utilized Differential evolution to improve the learning of k-means eSNN for a specific dataset. By arranging a particular number of clusters (k cluster). Recognizing the k centroids was the fundamental idea, one for each group. Relevant initialization of these centroids positions was needed because of the impact of delivering various results at various locations. Hence, it was favorable to put the points separated. Next, any point identified with specific datasets must be connected to the nearest centroid. The procedure was required to be copied until no point is anticipated. Therefore, it might be seen that the k centroids adjust their positions step by step until changes stopped. Finally, the procedure continues until limiting the squared blunder work which speaks to the target work in such circumstances. Afterward, the model was tested on 4 datasets. The experimental results show k-DESNN execution of clustering accomplished through the model using datasets, liver, Iris wine, and appendicitis. The accuracy measure of k-DeSNN for the Liver, Iris, and appendicitis dataset is not good enough which is below 80%. The excellent performance accuracy of k-DeSNN was 93.18% for the wine dataset.

Model of NHS-eSNN[26], the backpropagation (BP) method is used to enhance the normal algorithm convergence. The pre-synaptic neuron was considered as a candidate by eSNN. Also, both HS and BP are integrated with eSNN to find out the fitness evaluation and the schemes of mating selection. Initially, NHS-eSNN collects, normalizes, and reads the dataset. Furthermore, both candidate size and iteration maximum number are set. Moreover, eSNN pre-synaptic neurons are determined at random. The population of the new proposed algorithm is then created and initialized. After that, for each iteration, each candidate is evaluated based on the enhanced HS algorithm. The proposed algorithm ends after the maximum iterations are attained. The findings of the study demonstrate that NHS- eSNN can give better performance results in accuracy for Iris which is above 90% but for the rest of 5 datasets, the accuracy measures are below 80%.

3.1.4. Dynamic eSNN

The presented ESNC in [11] was one-pass learning. The decision of training samples ultimately affects ESNC performance. Therefore, the sequence of similar training samples in the network somehow leaves impact on the classifier's performance. Right after each training epoch, the parameter value was fixed, and datasets were fed into the network. In the presented algorithmic model, a supervised learning rule was used to modify synaptic weights joining hidden and output layer neurons. As a consequence, the sub-cluster produced in the hidden layer will be sent to the suitable neuron of the output layer. The result of the study shows that the purposed classifier ESNC (evolving Spiking Neural Classifier) performed well on Wisconsin Breast Cancer (WBC), Ionosphere, and Iris with accuracies of 97%, 98%, and 96.7% respectively. But could not provide good accuracy on Diabatic and Liver datasets (i.e. 65% and 58% respectively).

3.2. Evaluation Metrics(part II): Classification Accuracy

In this section, the performance accuracy of eSNN models under different variants is discussed. This section particularly describes the results of models tested from different datasets from the UCI Machine Learning Repository.

3.2.1. Hybridization of eSNN

The model presented in the study[27] used MLFF(multi-layer feed-forward) ANN to identify the exact disturbance type. The proposed system works on data choose by researchers, the data is traffic oriented and classified based on result type. First, the classification is conducted on 9 features, if the classification by eSNN is usual then the process repeats for 11 features. Yet again, if the classification was regular, then the machine would stop. But if the classification result was anomalous, then a two-layer feed-forward network was applied for pattern recognition of the outbreak type. Later, the analysis of the dataset, eSNN classifications, and pattern recognition was conducted. There are two classification cases; the first classification was on RAF Read Full data and the second one is normalFull data In both cases, the data are classified as normal or abnormal. The dataset T has 145,738 records and 70% (102,016rec.) used as train data and 30% (43,722rec.) used as test data. In the second case. The dataset has 145,738 records and 70% (102,016rec.) were used as train data and 30% (43,722rec.) used as test data. The obtained result was compared with 10 separate classifiers (NaiveBayes, MLP, k-NN, BayesNet, J48, RBFNetwork, RandomForest, AdaBoost, LogisticRegression, LibSVM) are shown below:

Table 3: eSNN Accuracy for Anomaly and Intrusion Detection Approach.

Classifier	Red Dataset	FullNormalFull dataset
NaiveBayes	95.4%	98.9%
RBFNetwork	93.3%	99.4%
MLP	97.4%	99.9%
LibSVM	97%	99.1%
KNN	97.4%	98.9%
RandomForest	97.5%	98.9%
LogisticRegression	96.9%	98.9%
BayesNet	96.9%	98.9%
AdaBoost	95.9%	98.3%
eSNN	97.7%	99.9%

3.2.2. Results: Modification of eSNN

According to the network presented in the study [10] parameters that were used in network training, fluctuates depending on the dataset. The first parameter used in this research denotes the number of receptive fields (P) and should be in between a range of 5 to 11. The second parameter λ denotes the overlap factor which was responsible for controlling the overlap between receptive fields. Overlap regulates the receptive field's width and it also affects firing time function. λ value was taken 3, which means that the overlap was 30% between two succeeding receptive fields. The third factor λ denotes the slope of the amplitude function f(). Although there were few other parameters k, α, and β that are responsible for the learning performance of the model. The parameter α was a threshold fraction, β was a constant, responsible for controlling neuron addition at the output layer. Factor k controls neuron depression and if somehow during the training the neuron was fired wrongly, then corresponding weights would cause a long-term depression. According to achieved accuracy by all the models (Logistic Regression, Multilayer Perceptron, Classification, And Regression Tree) compared in this study, it shows that eSNN has not improved much by the accuracy of 92%. On the other hand, the GP(Genetic Programming) model still proves itself as the best with an accuracy of 99.5%.

Table 4: eSNN Performance comparison with Other Iterative Methods.

Models	Accuracy
GP	99.50%
eSNN	92.50%
LR	89.50%
MLP	84.50%
CART	92%

The results stated in the paper [31] show HFSNN performance in a supervised learning manner, carried out in different scenarios and proposed evidence for evolving learning. HFSNN can solve various challenges in unpredictable adaptive learning environments. Nevertheless, its performance accuracy cannot be authentic as it has not been tested on real applications and there are numerous parameters utilized in the work which requires further investigation to improve the presentation of HFSNN. In on-line mode, HFSNN was applied on various benchmarks, where the information was fed into groups. That is, for every benchmark, the information was fed consecutively (1% of the information at each step). The execution of HFSNN was evaluated by applying testing data for each dataset that was held out. The results demonstrated that for certain benchmarks like cod—rna, german—number, and phishing, HFSNN optimizes on new data and has the option to improve the accuracy. For different benchmarking

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datasets, it catches the main pattern from information and varies around specific values. In such cases, the new data don't have a lot of relevant information, for example, the new models were the same as those which were already fed to HFSNN. Accordingly, there was not any noticeable accuracy improvement. In testing results from the offline mode of HFSNN, all samples were given one by one to HFSNN. By, utilizing various benchmarks for HFSNN, it performed well in comparison with other normal ML algorithms. Precisely, HFSNN beats other ML algorithms such as german numbers and skin/nonskin datasets, while accomplishing average for different benchmarks. HF- SNN did not show any off—the—run results for all of the benchmarks. In online mode, HFSN shows good accurate results for all six detests i.e. more than 80%. And for offline mode testing HFSN shows good accuracy for cod rna, mushroom, phishing, and skin nonskin datasets which is more than 80%. Nonetheless, for the rest of the two datasets namely ijcnn1 and german-numbers, the accuracies of HFSN in offline mode are 63% and 79%.

Table 5: HFSN Accuracy for Online and Offline Mode.

Datasets	online Mode	offline mode
ijcnn1	83.70%	63%
cod rna	85%	92%
mushrooms	100%	100%
german numbers	89.10%	79%
phishing	97.70%	96%
skin nonskin	92.10%	100%

3.3. Evaluation Metrics: Root Square & Root Mean Square

3.3.1. Dynamic eSNN

In the study [29], the performance accuracy of the presented model was tested on Data from Madrid city. Provided data was put into two sets, for testing and training phase. For NeuCube parameters tuning, training data was used. Drift, Refractory Time, STDP rate, Similarity, and Mod were the Neucube parameters used for the experiment. Genetic optimization tool was used to get optimal parameter values, which were provided by the NeuCube platform. Once optimal parameter values were found, NeuCube and deSNN were trained. Using 10-fold cross-validation, for deSNN's predictive results in terms of R2 and Root Mean Square Error were presented in this paper. The predictive results of the presented deSNN model show improved performance in comparison with other regression models. The deSNN was compared against selected machine learning algorithms that were frequently used for solving traffic forecasting issues, are as follows: AdaBoost regression (ADAR), k-nearest neighbors (KNN), random forest regression (RFR), gradient boost regression (GBR), decision tree regression (DTR), support vector machine(SVR), ridge regression (RID), extreme learning machine (ELM), and stochastic gradient descent regression(SGD).

Table 6: deSNN Accuracy For Road Traffic Estimation.

Models	R^2	RMSE
KNN	0.89	171
DTR	0.91	155
RFR	0.93	138
ADAR	0.91	153
GBR	0.92	144
RID	0.91	150
SGD	0.92	147
SVR	0.91	150
ELM	0.9	157

3.3.2. Modification of eSNN

In [32] eSNN was tested for classification suitability and few classifiers have been chosen to perform the comparison. The examined classification models, that depend on a broad learning algorithms range, namely: Multinomial Logistic Regression (MLR), Stochastic Gradient Descent (SGD), Support Vector Machine Classifier (SVC), Multilayer Perceptron (MLP), and K-Nearest Neighbors (KNN). These algorithms intervene during the classification phase of the system, by replacing the eSNN classifier thus giving labels to classes for days that were utilized to relegate traffic flow as long-term estimations. They tuned hyperparameters by cross-validation for the training dataset. The determination coefficient R2 (which denotes the probability of real values to fall inside anticipated ones) and Normalized RMSE (root mean squared error) were used in order to compare performance results. The results show that two methods obtained the same performance as eSNN – namely MLR, MLP, and SVC. On the contrary, SGD and KNN with higher RMSE values show that they are not acceptable with enough accuracy.

Table 7: eSNN Accuracy For Adaptive Long-Term Traffic Estimation

Models	R2	RMSE
eSNN	0.79	0.1
MLR	0.77	0.23
MLP	0.72	0.24
SVC	0.71	0.22
SGD	0.49	0.35

3.4 Theoretical Results Evaluation

3.4.1. Dynamic eSNN

The performance accuracy of the model presented in the study [28] was measured by applying the model for two different scenarios: (1) Moving object recognition through Address-Event Representation (AER) and (2) EEG SSTD recognition for brain-computer interfaces. According to the result purposed, the proposed model MODE achieved good accuracy when it is applied to moving object recognition tasks i.e. 90% with only 1 training iteration. Whereas for EEG of SSTD, it shows 83.33% accuracy although training iteration is the same as of moving object task.

3.4.2. Modification of eSNN

In the results of the study [30], The proposed QPSO-eSNN technique was tested utilizing the uniform hypercube dataset. To perform the execution, 10-folds cross-validation was applied. Only two of the ten features created were applicable in output class determination. According to experiments the position of the important characteristics directly affects the Threshold. Various receptive field values for different datasets affected the result accuracy. The three eSNN parameters should be optimized by QPSO. The eSNN-PSO algorithm was enormously dependent on parameter optimization due to which affecting results. During the testing phase, the obtained accuracy for eSNN-PSO was 80% to 90% as compared to QSPO-eSNN. The authors claimed the experiments show that the parameter optimization using QPSO was done within 80 iterations. Whereas the eSNN average accuracy with feature optimization was reliably above 90% in contrast with eSNN utilizing all features whose mean precision attests towards 60%. In the final case, the network could not respond to the repetition presented by the unimportant features. In this research, QPSO figured out how to optimize binary string data, which demonstrates expected eSNN parameter values. In the fundamental examination, we found that the Mod value should range between 0.6 and 1.0. QPSO figured out how to come out with the Mod value in between the specified range for the experiment. With the important features positioned at the last two stages, the result shows that the normal C values calculated in this analysis should be around 0.8, which could be satisfactory. In the end, the average Sim value was discovered to be 0.1 that is genuinely sufficient since the weight values were comparable between input samples in a similar class.

4. CONCLUSION

The evolving Spiking Neural Network is derived from one of the prominent SNN architecture. This model is believed to be an auspicious technique due to its simplicity competent neural model and rapid one-pass learning. However, the fundamental problem encountered in eSNN is that the selection of the hyperparameters needs to be done since deciding the optimum value for the parameters for a dataset is crucial. In this study, we review optimized eSNN models only for the supervised learning paradigm. Under supervised learning criteria, there are two types of tasks i.e., classification and regression. From the literature, we have found that most of the eSNN optimization was done for classification tasks. After a deep insight into the literature related to hyper-parameter optimization and their impact on the learning process of eSNN, it is observed that three parameters show a great influence on the learning process of the network. They are known as the Mod (modulation) factor, C (threshold), and Sim (similarity) factor. Mod controls the starting weights which influences the contribution of every spike to postsynaptic potential. Based on the literature, it is concluded that the Modulation factor should lie between the range of 0 and 1. It is found that if the mod value is near to 1, then spike contribution to post-synaptic potential would be a steady exponential function, while smaller values would cause the degraded exponential contribution. Subsequently, 0 value of mod would suggest that post-synaptic potential would not be influenced by presynaptic spikes. Similarly, if the mod value is 1, then it shows that all spikes' contributions will be equal to postsynaptic potential. The mod factor decides how strongly the request for spike timing influences a neuron. Sim represents the value on which output layer neurons would update or create. Through the literature, we concluded that if the weights of a newly created neuron are the same as the specified similarity value, then the neuron gets merged with the most similar neurons in the repository. The value of sim should lie between 0 and 1. A lower similarity value creates few numbers of neurons and a higher value would lead to overfitting by creating an output neuron for each input sample. The Threshold factor is the fraction of maximum PSP. It is calculated by utilizing a parameter C with a value somewhere in the range of 0 and 1. Fraction C with lower values would result in a reduced firing threshold which in return advances neuron response. Hence, in our opinion, the hyperparameters influences the segregation outcome, the eSNN capability, and also is reliant on data to be categorized, further improvement of the model is necessary for terms of optimizing its parameter. However, there are some other parameters of eSNN architecture that are studied and optimized in previous work, but they were failed to show a prominent role in the network learning process. The eSNN model is unable to find its own parameter optimal value.

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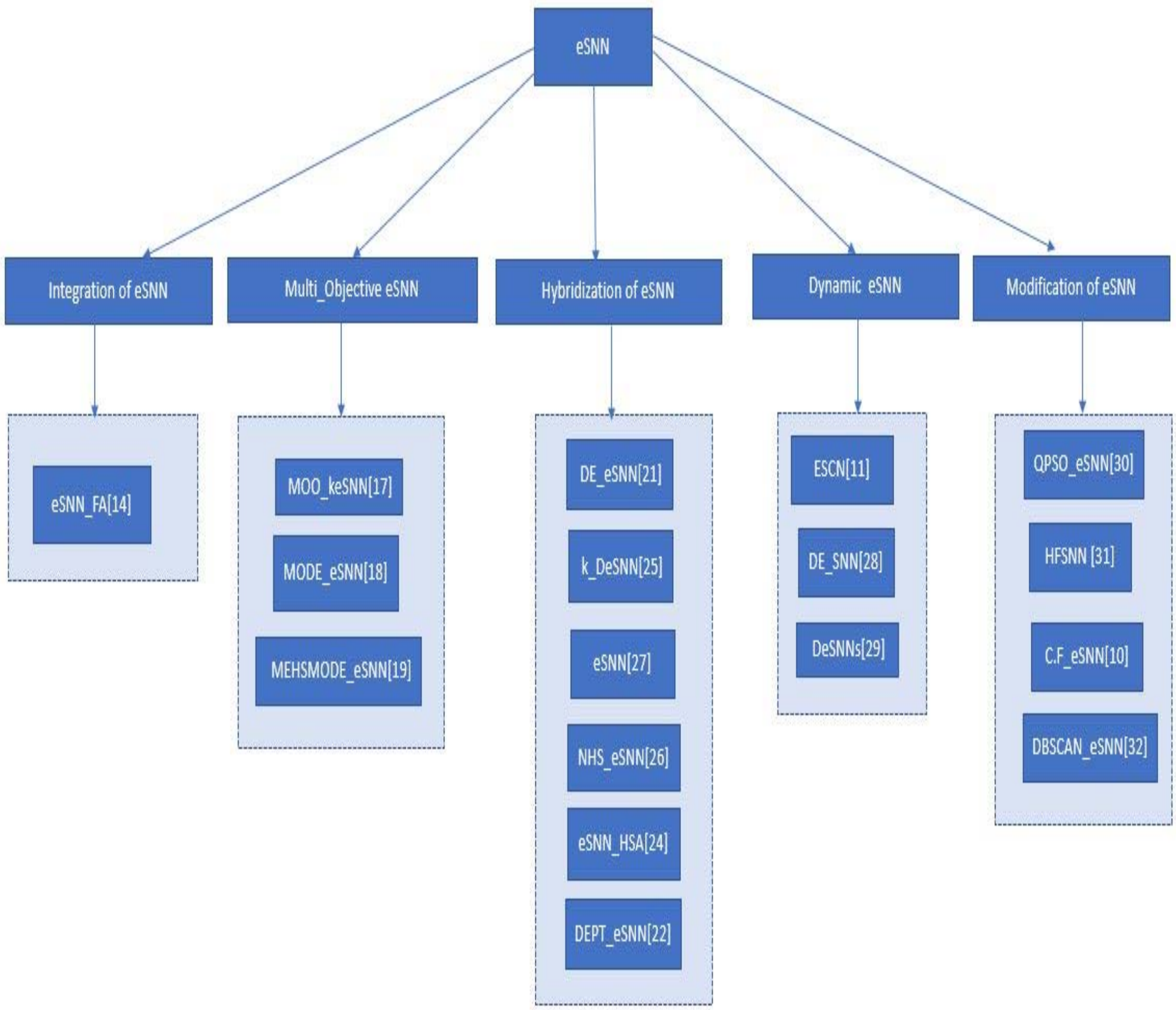
eSNN
Integration of eSNN
Multi_Objective eSNN
Hybridization of eSNN
Dynamic eSNN
Modification of eSNN
eSNN_FA[14]
MOO_keSNN[17]
MODE_eSNN[18]
MEHSMODE_eSNN[19]
DE_eSNN[21]
k_DeSNN[25]
eSNN[27]
NHS_eSNN[26]
eSNN_HSA[24]
DEPT_eSNN[22]
ESCN[11]
DE_SNN[28]
DeSNNs[29]
QPSO_eSNN[30]
HFSNN [31]
C.F_eSNN[10]
DBSCAN_eSNN[32]

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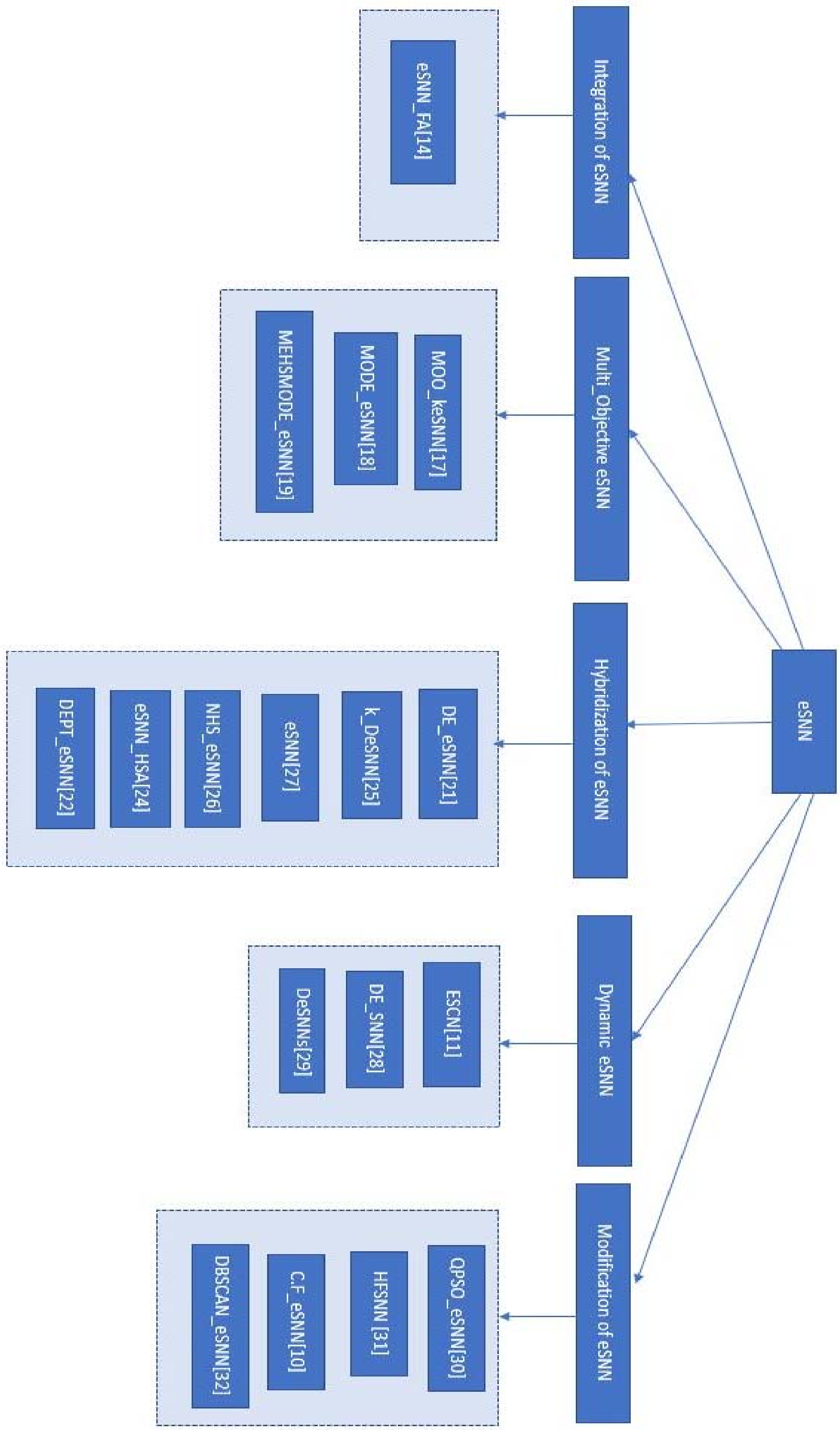

Fig. 5: Flow Chart of eSNN Models categorized in variants

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Table 1: Summary of eSNN Models Reviewed in this Study

Model	Author	Contribution	Variant Category
ESNN-FA [14]	Farezdzuan Roslan, Haza Nuzly Abdull Hamed and Mohd Adham Isa	The coordination between ESNN (Evolving Spiking Neural Network) and FA (Firefly Algorithm) for ESNN parameter optimization was presented in this study. Since ESNN requires automatic parameter selection, so FA, as a metaheuristic algorithm was utilized as another parameter optimizing agent for ESNN.	Integration
MOO-keSNN [17]	Haza Nuzly Abdull Hamed, Abdulrazak Yahya Saleh, and Siti Mariyam Shamsuddin.	A model MO-KESNN (multi-objective K-means evolving spiking neural network) was introduced in this study. It was applied for the clustering problem based on the differential evaluation. To improve ESNN, K-means has been used. The presented model advances ESNN flexibility in delivering better solutions that can further apply to overcome drawbacks of the K-means mechanism.	Multi- objective
MODE-ESNN [18]	Abdulrazak Saleh, Siti Shamsuddin, and Haza Hamed	They employed MOO for ESNN hybrid learning to select the ideal pre-synaptic neurons and for problems related to classification performance accuracy	Multi- objective
MEHSMODE-ESNN [19]	Abdulrazak Yahya Saleh, Siti Mariyam Shamsuddin and Haza Nuzly Abdull Hamed	The proposed model MEHSMODE-ESNN (Mimetic Harmony Search Multi-Objective Differential Evolution with Evolving Spiking Neural Network) to decide the ideal number of presynaptic neurons and parameters for given datasets simultaneously. A memetic approach with Harmony Search (HS) algorithm was applied to improve MOO performance with ESNN.	Multi- objective
DE-ESNN [21]	Abdulrazak Yahya Saleh, Haza Nuzly Bin Abdull Hameed and Mohd Najib Mohd Salleh	An innovative hybrid DE-ESNN was proposed in this study to discover the most appropriate pre-synaptic neurons for a given dataset. It is required before ESNN starts learning. They applied DE as one of the EAs for parameter values selection.	Hybridization
DEPT-ESNN [22]	Abdulrazak Yahya Saleh and Siti Mariyam Shamsuddin	In this analysis, a hybrid model (DEPT-ESNN) based on differential evolution was implemented for the optimization of ESNN variables. The best estimates of variables were efficiently chosen by DE to eliminate an incorrect selection of model parameters by trial and error method for specific issues.	Hybridization
ESNN-HSA [24]	Zulhairi Mi Yusuf, Haza Nuzly Abdull Hamed, Lizawati Mi Yusuf and Mohd Adham Isa	In classification, the ESNN model behaves as a classifier. It requires optimization for its important parameters. However, the parameters are expected to tune by manual setting before the classification process begins. To tackle this issue, an optimizer was needed by ESNN for parameter optimization. The best parameter estimations were adaptively chosen by Harmony Search Algorithm (HSA). Therefore, this article proposed the combination HSA as optimizer and ESNN as a classifier for the optimization of parameters	Hybridization
K-DESNN [25]	Abdulrazak Yahya Saleh, Haza Nuzly Bin Abdull Hamed, Siti Mariyam Shamsuddin and Ashraf Osman Ibrahim	A new hybrid K-DESNN for clustering issues was established by integrating D.E and K-means with evolving spiking neural networks (K-means ESNN). The proposed model inspects that ESNN improves by utilizing the K-DESNN model. This methodology improves the adaptability of the ESNN in giving better results. Further, these results can be used to overcome drawbacks from K-means algorithm.	Hybridization
NHS-ESSN [26]	Abdulrazak Yahya Saleh, Siti Mariyam Shamsuddin, Haza Nuzly Bin Abdull Hamed, The Chee Siong, and Mohd Kamal bin Othman	A new model NHS_ESNN for clustering issues was presented in this study. It was created by combining the harmony search algorithm with an evolving spiking neural network. HS has been utilized to improve the standard ESNN model. The presented new algorithm plays a powerful role in enhancing ESNN adaptability for better results production. It also helped in minimizing drawbacks of ESNN	Hybridization
eSNN [27]	Konstantinos Demertzis and Lazaros Iliadis	In this paper, we have proposed a Hybrid Evolving Spiking Anomaly Detection Model which intended to classify the normal and attack patterns in a computer network. This paper proposes a network-based online system, which uses minimum computational power to analyze only the basic characteristics of network flow, to spot the existence and the type of a potential network anomaly. It is a Hybrid Machine Learning Anomaly Detection System (HMLADS), which employs classification performed by Evolving Spiking Neural Networks(eSNN), to properly label a Potential Anomaly (PAN) in the net. On the other hand, it uses a Multi-Layer Feed Forward (MLFF) ANN to classify the exact type of the intrusion.	Hybridization

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Model	Author	Contribution	Variant Category
ESNC [11]	Jinling Wang, Ammar Belatreche, Liam Maguire and T.M. McGinnity	Contributes by presenting a novel RBF-like fast dynamic Evolving Spiking Neural classifier (ESNC). The prepared feed-forward SNN comprises of three layers of spiking neurons: an encoding layer which transiently encodes truly esteemed highlights into Spatio-temporal spike designs, a hidden layer of powerfully developed and pruned neurons to perform clustering in a spatiotemporal manner, and an output layer for the classification process.	Dynamic ESNN
deSNN [28]	Nikola Kasabov, Kushite Dhoble, Nuttapod Nuntalid, and Giacomo Indiveri	Presents another class of eSNN, named as dynamic eSNN, that uses dynamic synapses and ROC (request order) learning to learn SSTD in a quick, on-line mode. The paper likewise presents another model called deSNN, that uses SDSP spike-time and ROC learning in an unsupervised manner, supervised manner, or semi-supervised manner. The SDSP was utilized to dynamically evolve the connection weights that catch Spatio-temporal clusters of spike information both during preparing and during the review	Dynamic ESNN
QPSO-ESNN [30]	Maurizio Fiasché and Marco Taisch	This paper presents another combination technique for synchronous optimization of highlights and parameters in an ESNN utilizing QPSO beginning from a progressively broad QEA. In this paper we dissect a specific kind of SNN, the evolving SNN (eSNN), mostly concentrating on their weights, feature, and parameters optimization utilizing another evolutionary process. This study consolidates the ESNN structure with a QAE(Quantum inspired evolutionary algorithm), to explore the capability of ESNN when applied to Feature Subset Selection (FSS) issues following the wrapper approach.	Modification
ESNN for C.F[10]	Amit Soni Arya, Vadlamani Ravi, Vidalia Tejasviram, Neelava Sengupta and Kasabov	In this work, they have applied the spiking neural system to deal with identifying the phishing sites. With the fast development of the web, the greater part of the organizations is currently moving on the web. Since the web is universal and can be approached from anyplace. These websites are suspected of attacks. A phishing site attack is one of them. In these types of attacks, the attacker duplicates the website and attempts to act like a real to take the client's data. In this way, it is the most extreme need to identify such phishing sites.	Modification
deSNNs [29]	Ibai Lana, Elisa Capecci, Javier Del Ser, Jesus L. Lobo, and Nikola Kasabov	Presents another methodology for Spatio-temporal rad traffic forecasting that depends on the reception of the NeuCube structure founded on SNN. Exploiting the NeuCube features, this work pays attention especially to the potential of spatially aware traffic variable forecast, just as on the investigation of the Spatio-temporal connections among various sensor areas inside traffic arrange. Its presentation, surveyed over genuine traffic information gathered in 51 areas in the focal point of Madrid (Spain), is better than that of other ML strategies as far as determining precision.	Dynamic ESNN
HFSNN [31]	Obada Al Zoubi, Ahmad Mayeli, Mariette Awad and Hazem Refai	Here, the term Evolving learning (EL) was introduced, to gaining from new information and inconspicuous before classes without expecting to re-train models as in conventional ML techniques. To accomplish the objective of EL, they acquire a paradigm which is biologically inspired, to fabricate a highly versatile supervised learning mode dependent on two brain-like data handling: First is the hierarchical abstraction and second is divide and conquer. Besides, the proposed method, which they named as HFSNN (Hierarchical Fusion Evolving Spiking Neural Network), utilizes a biologically inspired and dynamic spiking neural system (SNN) with the upgraded neural model.	Modification
ESNN with DBSCAN [32]	Ibai Laña, Jesus L. Lobo, Elisa Capecci, Javier Del Ser and Nikola Kasabov	This work presents a technique to get long-term forecast patterns and adjust them to ongoing conditions. To this end, long- term estimation plan dependent on the pattern automated discovery was proposed and coordinated with adaption and online change detection mechanism. The structure takes benefits of eSNN to perform adjustments without retraining the model, permitting the entire framework to work independently in an on-line style. Its achievement was evaluated over a real situation with 5 min information on 6-month traffic in Madrid, Spain	Modification

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Table 2: Performance Accuracy of eSNN Models

Hepatitis	-	- %	52%	59%	52%	55%	-	-	60%	-
Haberman		-	72%	76%	-	73%	-	-	78%	-
Appendicitis	-	72%	73%	76%	-	68%	-	78%	77%	-
Ionosphere	-	-	70%	64%	71%	62%	-	-	67%	98%
Liver	-	-	51%	57%	-	44%	-	78%	56%	58%
Wine	79%	94%	-	-	-	-	67%	93%	-	-
Heart	78%	-	58%	59%	63%	66%	74%	-	60%	-
Diabetes	68%	-	-	-	-	-	56%	-	-	65%
Breast Cancer	92%	-	-	-	91%	-	94%	-	-	98%
iris	84%	77%	90%	91%	93%	89%	90%	70%	95%	97%
Models	ESNN-FA[14]	MOO-keSNN [17]	MODE-eSNN[18]	MEHSMODE-eSNN[19]	DE-eSNN [21]	DEPT-SNN [22]	eSNN-HSA[24]	K-DeSNN[25]	NHS-eSNN[26]	ESNC[11]