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Unveiling the Impact of Extreme Learning Machine in the Defence and Military Sector

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ABSTRACT

Among the most well-known machine learning algorithms, Extreme Learning Machine (ELM) has seen widespread use across a variety of fields, including the defence and military industries. For problems like sluggish technique and iteratively altering the hidden layer's parameters to optimise the efficiency of the gradient descent approach, a cutting-edge machine learning algorithm known as the ELM has been developed. Depending on the specific objective and circumstance, the Extreme Learning Machine (ELM) may be more appropriate than Deep Neural Network (DNN) techniques. The models constructed in this manner perform quite well in generalisation. The following three goals are emphasised in its unconventional structure: 1) A great degree of accuracy in learning 2) less need for direct human involvement 3) an extremely rapid rate of learning, and moreover, it provides an optimal response for the whole world. As a result of its quick training, flexibility, and resilience, the Extreme Learning Machine (ELM) has several uses in this field, including target detection and tracking, image and signal processing, cybersecurity and intrusion detection, decision support systems, pattern recognition and classification, etc. According to our findings, the ELM approach was used with low training time and the testing accuracy is excellent. Also, this study presents the contribution of the revolutionary machine learning algorithm ELM to the defence and military sectors.

Keywords: Predictive analytics; Cyber security; Robotics; Real-time processing; Target detection

NOMENCLATURE

DNN	: Deep Neural Network
RBF	: Radial Basis Function
HELM	: Hierarchical Extreme Learning Machine
CELM	: Convolution Extreme Learning Machine
DS	: Data Streaming

1. INTRODUCTION

When it comes to national security, personnel safety, and mission success, defence and military operations rely heavily on swift and precise decision-making. The ELM system is a potent resource for real-time analysis of massive amounts of complicated data, prediction, and the identification of targets or threats[1,37]. In order to detect threats, identify anomalies, and understand the current situation accurately, the capacity to handle faulty data and adapt to new circumstances is essential. It improves overall situational awareness, operational efficiency, and risk mitigation, as well as reducing risk, protecting key infrastructure, and optimising the use of resources by utilising the power of machine learning.

The specific use case determines if ELM or other techniques should be used. When dealing with huge datasets, ELM is especially helpful for situations where quick training and effective processing are essential. Even though they may need more processing resources and significant hyper parameter tuning, existing techniques like neural networks, SVMs, and decision trees are useful for situations where interpretability, flexibility, and sequential data analysis are critical[2-4, 34].

The classical or standard technique for ELM (shown in Fig. 1 and included in the notations for Table 1) is as follows: In the first step, initialise the parameters using the provided training data. Making adjustments to the activation function as well as the number of hidden nodes is also part of this process (x,t). A random value (b) is then allocated to the hidden layer, and weights (w) are also assigned in step 2. In the third phase, the resulting matrix from the hidden layer is calculated using the formula H=hij=g($wjxi$+bj), with i=1,2,…,N and j=1,2,…,K, respectively.

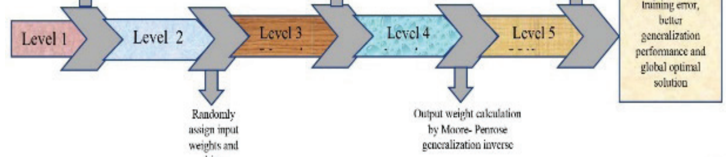

Figure 1. ELM standard procedure.

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Table 1. Notations

Notation	Meaning
X_i	Input vector of the ith sample
t_i	Target vector of the ith sample
$g(x)$	Activation function
$\tilde{N}$	Hidden node's counts
W_j	Input layer to jth weighted hidden node's
b_i	ith hidden bias of a node
H	Matrix representing the output from the hidden layer
h_{ij}	Matrix representing the hidden layer's output, which contains the ith sample and the jth hidden node
B	Resulting Layer Weight Matrix
H^t	Matrix H Moore-Penrose generalised inverse
T	Resulting Layer Matrix
λ	Scaling factor
H^T	Transpose of matrix H

The subsequent step entails output weight determination ($\beta = H^{\dagger} T$ in the generic case; if training data exceeds hidden nodes, then; $\hat{a} = \left(\frac{1}{\lambda} + H^T H\right)^{-1} H^T T$ alternatively, if there is less training data than hidden nodes, then $\beta = H^T \left(\frac{1}{\lambda} + H H^T\right)^{-1} T$). In the end, the calculation of the ELM network is complete[5–9].

The defence and military industries have benefited as a result of ELM (Extreme Learning Machine) implementation, a powerful and adaptable machine learning technology. When it comes to improving processing speed, pattern recognition, and field decision-making, ELM's rapid learning, versatility, and resilience make it an indispensable tool for defence organisations.

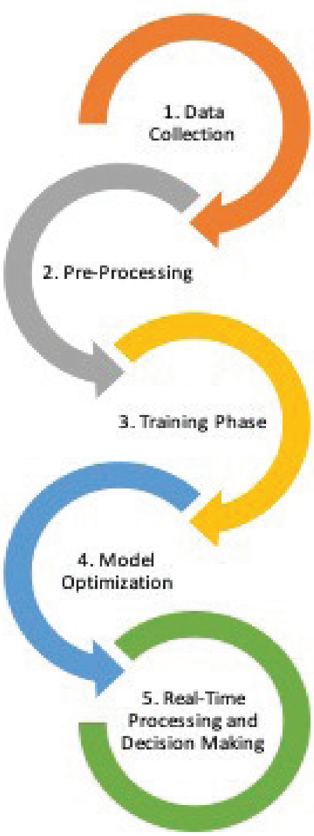


Figure 2. Process flow diagram of ELM in defence and military sector.

2. WORKFLOW OF ELM IN DEFENCE AND MILITARY SECTOR

Extreme Learning Machines (ELM) has a multi-step process that must be followed for them to operate in the defence and military sectors (Fig. 2). An abbreviated version of the steps is as follows:[10-13, 34-37]

- Step 1: **Data Collection -** Data that is pertinent to the investigation is compiled from a wide variety of resources, including sensors, satellites, surveillance systems, and communication networks, amongst others. This information may contain details about the targets, objects, surroundings, and any other relevant aspects
- Step 2: **Pre-Processing -** The gathered information is then pre-processed in order to eliminate noise, account for missing values, and standardise the features. During this stage, the data will be converted into a format that is appropriate for training the ELM model.
- Step 3: **Training Phase -** (a) **Input Layer** - The data, after being pre-processed, is then sent into the ELM model's input layer, which is composed of neuron representations of each feature and input.
  (b) **Hidden Layer**: The weights are arbitrarily selected for the links between the input layer and the hidden layer. The weighted inputs are subjected to a nonlinear activation function throughout the hidden layer's processing. This function might be a sigmoid or a Radial Basis Function (RBF), for example.
  (c) **Output Layer**: The hidden layer contains neurons that communicate with the output layer, which is responsible for making the ultimate predictions or classifications. The different activation functions might be used by the neurons in the output layer, depending on the particular job at hand. For example, Softmax may be used for classification issues, whereas linear activation may be used for regression tasks.
- Step 4: **Model Optimisation**: It may be necessary to tune the model's parameters, such as the number of hidden neurons and the activation functions, to get optimal performance. In this stage, the ELM model is fine-tuned depending on the particular defence and military application requirements that have been gathered. Finding the ideal values for one's hyper parameters may be accomplished through the use of methods such as cross-validation and grid search.
- Step 5: **Real-time Processing and Decision Making**: Once the ELM model has been trained and optimised, it may be deployed for real-time processing in defence and military applications. The trained ELM model is provided with new data or inputs, which are then processed by the network to arrive at predictions or conclusions depending on the activity that is currently being performed. This can involve the identification of targets, the detection of threats or anomalies, or the provision of decision assistance.

  It is crucial to note that the real implementation and system architecture may differ based on the specific defence and military application, as well as the integration of ELM with other components or systems. This is something that should be taken into consideration when planning the actual implementation.

3. IMPORTANCE OF ELM IN DEFENCE AND MILITARY SECTOR

Extreme learning machines provide a number of benefits, which contribute to their continued relevance and significance in the defence industry. The following are many major elements that show the importance of ELM in defence and the military[14–18].

3.1 Fast and Efficient Training

In comparison to more conventional machine learning algorithms, the training procedure for ELM is straightforward and quick. Because it can swiftly train models despite the vast magnitude of the information being used, it is particularly useful in defence applications, which need real-time decision-making.

3.2 Real-Time Processing

The processing of vast amounts of data in real time is frequently required of defence and military systems. This data may include sensor readings, satellite pictures, or surveillance feeds. Because of its rapid training and prediction capabilities, ELM is ideally suited for real-time processing, which enables users to respond quickly to rapidly changing circumstances.

3.3 Robustness and Adaptability

ELM has demonstrated reliable performance when it comes to dealing with noisy or missing input. It is to ELM's benefit to be able to manage a variety of different circumstances, which is particularly helpful in defence-related contexts where the data quality may be affected by a number of different causes. In addition, ELM is capable of easily adapting to different settings, which makes it suited for use in dynamic defence applications.

3.4 Pattern Recognition and Classification

Tasks like target identification, object recognition, and threat categorization are essential components of defence and military operations. The capacity of ELM to properly conduct pattern recognition and classification tasks can be of assistance in determining whether or not a danger is present, differentiating between friendly and hostile things, and enhancing awareness of the surrounding environment.

3.5 Cybersecurity and Intrusion Detection

The development of intrusion detection systems to protect military networks and critical infrastructure can benefit from the utilisation of ELM. ELM may assist in discovering abnormalities and potential cyber threats by analysing the patterns of traffic on a network. This makes it possible to take proactive defensive measures to safeguard critical information and systems.

3.6 Decision Support System

ELM may be utilised to construct decision support systems, which can be of assistance in the execution of complicated military planning, the distribution of resources, and the formulation of strategic decisions. ELM has the ability to deliver significant insights to military leaders by analysing historical data and building prediction models, which in turn helps the commanders make better-informed decisions.

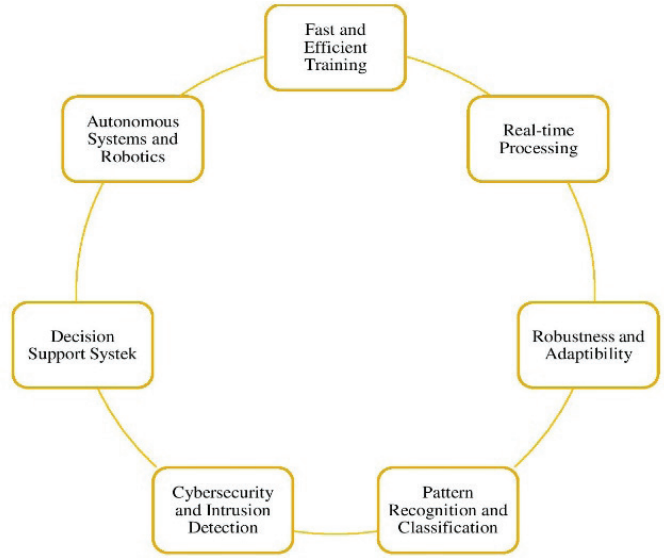


Figure 3. Role of ELM in defence and military application.

3.7 Autonomous Systems and Robotics

ELM has the potential to make a contribution to the growth of autonomous systems and robotics in the defence industry. Because of its rapid learning and prediction capabilities, it is well-suited for use in the real-time decision-making processes of unmanned vehicles, drones, or robotic systems that are working in dynamic and unpredictable situations.

3.8 Predictive Maintenance

By examining data from sensors and performance logs, ELM can reduce downtime and assist in predicting maintenance requirements for military equipment and vehicles.

3.9 Natural Language Processing

For the purpose of processing massive amounts of textual data for intelligence and communication analysis, ELM can help with the processing and understanding of natural language.

3.10 Situational Awareness

By combining and processing data from numerous sensors, ELM can enhance situational awareness, assisting military troops in making quick judgements.

Extreme learning machines are excellent tools for use in defence and military applications because of their overall speed, efficiency, flexibility, and resilience. ELM has the potential to improve the capabilities of a wide variety of systems, ranging from cybersecurity to decision support, which will ultimately lead to an increase in the efficacy and efficiency of defence operations.

4. OPEN CHALLENGES WITH ELM

The following are the open challenges or ongoing research

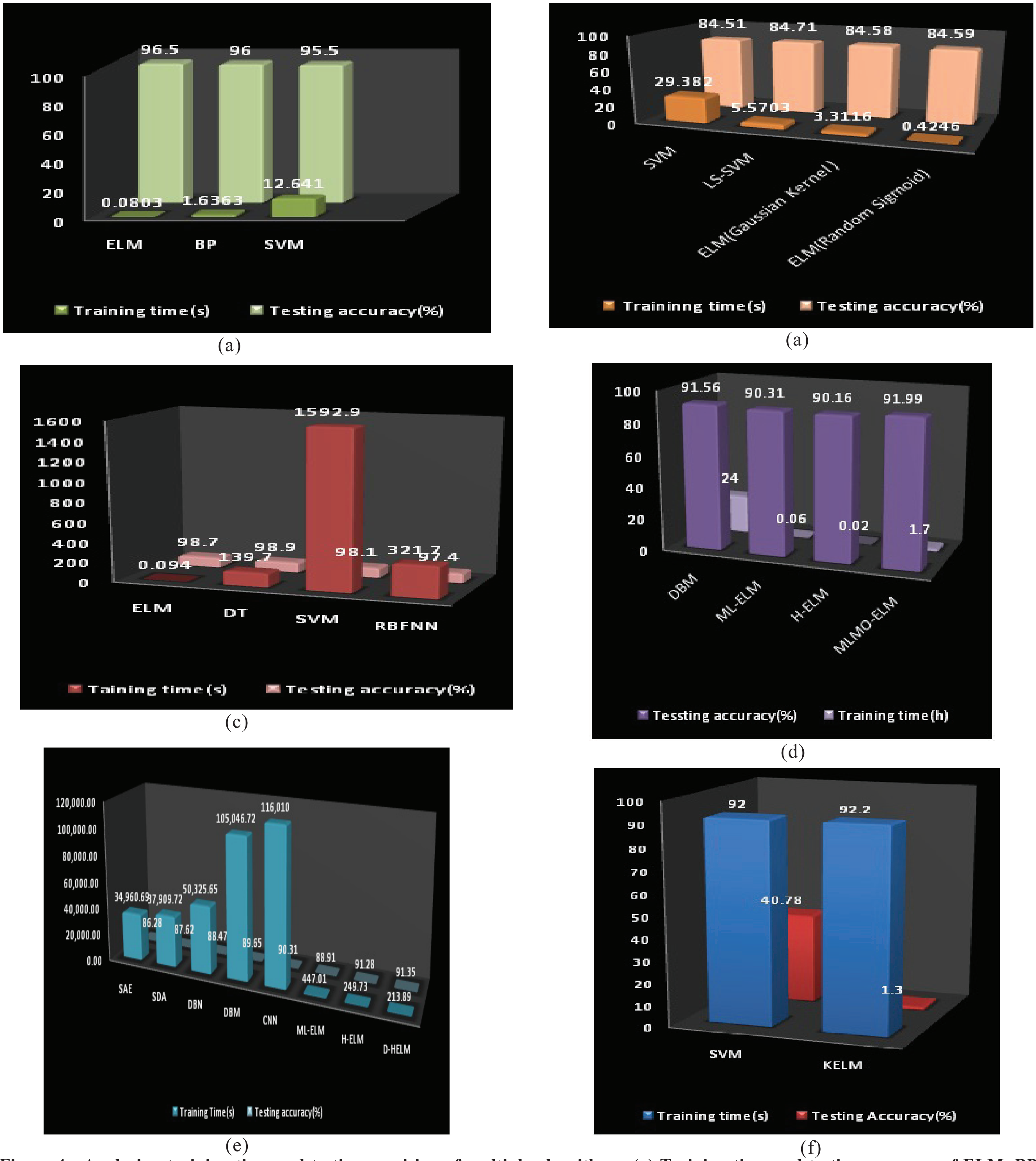
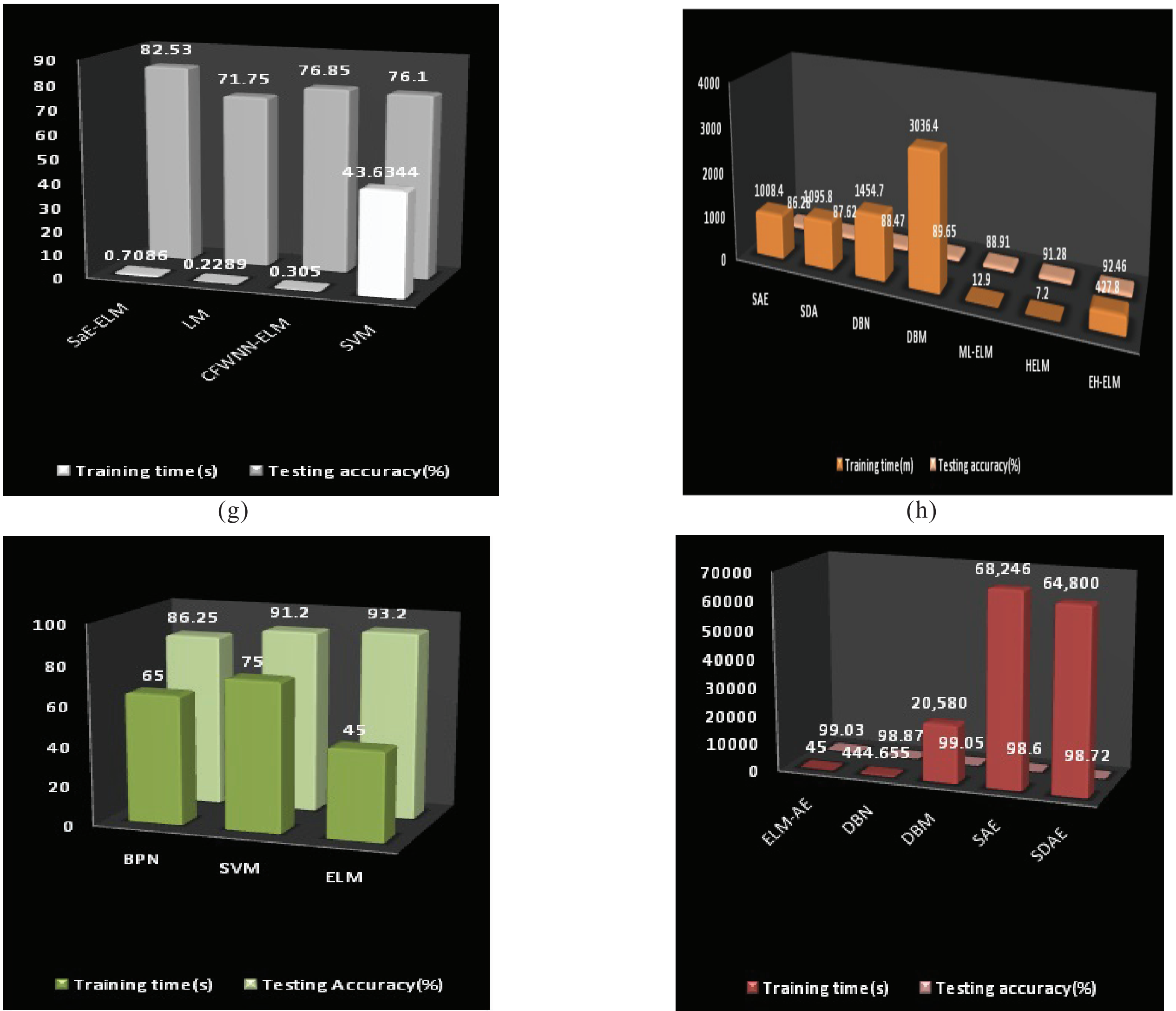


Figure 4. Analysing training time and testing precision of multiple algorithms; (a) Training time and testing accuracy of ELM, BP and SVM algorithms; (b) Training time and testing accuracy of SVM, LS-SVM and ELM algorithms; (c) Training time and testing accuracy of ELM, DT, SVM, RBFNN algorithms; (d) Training time and testing accuracy of DBM, ML- ELM, H-ELM and MLMO-ELM algorithms; (e) Training time and testing accuracy of SAE, SDA, DBN,DBM,CNN,ML-ELM,H-ELM and D-HELM algorithms; and (f) Training time and testing accuracy of SVM and KELM algorithms.

areas in the future direction associated with ELM in defence and military applications[19-23, 35].

- It still struggles to handle complex and dynamic environments.
- Data Limitations and Imbalance: Military and defence datasets are often restricted, imbalanced, or much specialised, making ELM model training difficult.
- Large data streams or high-resolution sensor inputs



(g) (h) (i) (j)

Figure 4. Analysing training time and testing precision of multiple algorithms; (g) Training time and testing accuracy of SaE-ELM, LM, CFWNN AND SVM algorithms; (h) Training and testing accuracy of SAE, SDA, DBN, DBM, ML-ELM, HELM AND EH-ELM algorithms; (i) Training time and testing accuracy of BPN, SVM and ELM algorithms; and (j) Training time and testing accuracy of ELM-AE, DBN, DBM, SAE and SDAE algorithms.

demand real-time processing and scalability in defence and military applications. To achieve these objectives, ELM methods must be computationally efficient and scalable.

- ELM models must be resilient to hostile inputs or data manipulations to protect defence applications because these systems are vulnerable to adversarial assaults that exploit weaknesses.
- The fundamental decision-making mechanism of ELM models can be hard to understand especially those with deep architectures or complicated network configurations, because of their lack of interpretability.
- Compatibility, interoperability, and the necessity to deal with legacy systems add complexity to the process of integrating ELM algorithms into pre-existing defence and military infrastructure.
- Trust in the ELM decision-making process and establishing efficient human-machine collaboration are crucial obstacles to overcome.

The defence and military industries may greatly benefit from ELM if these obstacles can be overcome.

6. RESULTS AND ANALYSIS

This section provides a detailed analysis and explanation of the ELM results, as well as proving the significance and applicability of the findings as shown in Annexure I.

In all cases, according to the results of our analysis, where the ELM technique was adopted at the expense of little training time, the testing accuracy is excellent and exhibit low complexity. The model design, data size, and the availability of labelled data are other factors that affect how effective they are. However, there are several indications as to when ELM may be preferable over other DNN techniques, including training speed, simple architecture, memory efficiency etc.

7. RECOMMENDED MODELS

There are four recommended models that could be useful in most applications and could handle some of the challenges that come with them:

- Binning with HELM (binning with hierarchical ELM)- By minimising noise and non-linearity in the dataset, binning increases the accuracy of predictive models. Finally, binning makes it simple to spot outliers, invalid, and missing numerical data. Binning is a machine learning quantization approach for dealing with continuous variables. So, the combination of binning with HELM may give wonderful results.
- Pruning, compaction, or quantization with CELM (pruning, compaction, or quantization with convolution ELM) - Employing techniques like pruning, compaction, and quantization in convolution layers of the convolution extreme learning machine may help speed up the learning.
- Gamma classifier with ELM (Gamma classifier implementation with ELM) - The proposed technique can cope with the space and time constraints that data stream scenarios impose. To detect idea drift and provide a forgetting mechanism, the Data Streaming Gamma Classifier (DS-Gamma classifier) uses a sliding window technique. Several experiments were carried out to test the classifier, employing actual and synthetic data streams in various data stream circumstances.
- Fuzzy with HELM (fuzzy implementation with hierarchical ELM) - To take advantage of the powerful aggregation properties described by fuzzy techniques, we propose including fuzzy layers into the deep learning architecture. This combination has the potential to improve picture classification accuracy or handle imprecise and uncertain conditions.
- Polishing with HELM (polishing implementation with hierarchical ELM) - Both class and attribute noise can be removed by polishing, data scrubbing, or relabeling with HELM.

8. CONCLUSION

Extreme Learning Machines (ELM) have a lot of potential in the defence and military industries. Rapid training, adaptability, and resilience are just a few of the reasons why ELM is such a powerful tool for solving a broad variety of challenges in various domains. These machines are used in defence and military applications to increase situational awareness, give better insight, and facilitate better decision-making. As an evidence, when we analyse the results, the testing accuracy is high in all the cases which are adapted ELM technique at the cost of low training time. Also, their effectiveness is influenced by things like model architecture, data size, and the accessibility of labelled data. However, some insights on when ELM might be preferred over specific DNN techniques are: training speed, simple architecture, shallow learning, initialization independence and memory efficiency. Extreme Learning Machines (ELM) can have a lot of benefits for applications in the military and defence industry, but there are also certain unique problems and difficulties that must be taken into account such as data security and privacy, robustness and resilience, real-time decision making, human-machine interaction, adversarial attacks etc. This study would be helpful in other applications also, such as- intelligent and threat detection, optimized resource allocation, predictive maintenance, rapid data processing and analysis, anomaly detection in cyber security etc. Due to its many benefits, ELM is an attractive option for meeting the challenges and requirements of defence and military operations, helping to ensure their ultimate success.

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She was involved in critical review for intellectual content, reviewing of this work.

Annexure I

Comparative paper survey

Paper reference	Data set	Algorithm used	No. of hidden nodes	Testing accuracy (%)	Training time (s)	Activation function	Method complexity
[24] Fig. 4(a)	EEG images	ELM	10	96.00±0.50	0.0803	Squashing	Little
		BP	10	95.50±0.50	1.6363	Squashing	Huge
		SVM	------	95.25±0.25	12.6410	----------	Moderate
[25] Fig. 4(b)	Diabetes, Australian, colon, credit, colon etc...	SVM	1000	84.51	29.382	----------	Moderate
		LS-SVM	1000	84.71	5.5703	----------	Moderate
		ELM (Gaussian Kernel)	1000	84.58	3.3116	Gaussian	Little
		ELM (Random sigmoid hidden nodes)	1000	84.59	0.4246	Squashing	Little
[26] Fig. 4(c)	Dynamic security assessment	ELM	85	98.7	0.0942	Sine	Little
		DT	85	98.9	139.694	----------	Moderate
		SVM	85	98.1	1592.89	----------	Huge
		RBFNN	85	97.4	321.687	----------	Huge
[27] Fig. 4(d)	OCR	DBM	4000	91.56	>24h	Squashing	Huge
		ML-ELM	15200	90.31 % (± 0.13)	0.06h	Squashing	Moderate
		H-ELM	15400	90.16	0.02h	Squashing	Moderate
		MLMO-ELM	3200	91.99%± 0.06)	1.7h	Squashing	Moderate
[28] Fig. 4(e)	NORB	SAE	-------	86.28	34,960.69	Squashing	Moderate
		SDA	-------	87.62	37,909.72	Squashing	Moderate
		DBN	-------	88.47	50,325.65	Squashing	Huge
		DBM	-------	89.65	105,046.72	Squashing	Huge
		CNN	-------	90.31	116,010	Squashing	Huge
		ML-ELM	-------	88.91	447.01	Squashing	Moderate
		H-ELM	-------	91.28	249.73	Squashing	Moderate
		D-HELM	-------	91.35	213.89	Squashing	Moderate
[29] Fig. 4(f)	ATM, DIAS	SVM	---------	92.5, 92.0	1.30, 40.78	-----------	Moderate
		KELM	----------	94.1, 92.2	0.17, 1.30	----------	Little

Contd.

Annexure I

Comparative paper survey

Paper reference	Data set	Algorithm used	No. of hidden nodes	Testing accuracy (%)	Training time (s)	Activation function	Method complexity
[30] Fig. 4(g)	Disease, Iris, Wine, Protein sequence	SaE-ELM	18,18,22, 80	82.53, 97.20, 97.95, 97.53	0.7086, 0.2289, 0.3050, 43.6344	-----------	Little
		LM	20,10,20, 60	71.75, 95.40, 92.97, 87.45	0.3066, 0.3641,0.4988, 13.26	-----------	Moderate
		CFWNN-ELM	30,20,30, 130	76.85, 95.92, 95.15,87.48	0.0016, 0.0009, 0.0028, 0.0859	-----------	Little
		SVM	81,23,47, 261	76.10, 94.36, 97.48, 90.63	6.7094, 4.5488, 5.8941, 274.9672	-----------	Moderate
[31] Fig. 4(h)	NORB	SAE	-------	86.28	1008.4m	Squashing	Moderate
		SDA	-------	87.62	1095.8m	Squashing	Moderate
		DBN	-------	88.47	1454.7m	Squashing	Huge
		DBM	-------	89.65	3036.4m	Squashing	Huge
		ML-ELM	-------	88.91	12.9m	Squashing	Moderate
		HELM	-------	91.28	7.2m	Squashing	Moderate
		EH-ELM	-------	92.46	427.8m	Squashing	Moderate
[32] Fig. 4(i)	Harvard benchmark	BPN	34	86.25	65	-----------	Huge
		SVM	8	91.2	75	-----------	Moderate
		ELM	60	93.2	45	Squashing	Little
[33] Fig. 4(j)	MNIST	ELM-AE	10000	99.03	444.655	Squashing	Little
		DBN	10000	98.87	20,580	-----------	Moderate
		DBM	10000	99.05	68,246	-----------	Huge
		SAE	10000	98.6	>17h	-----------	Moderate
		SDAE	10000	98.72	>17h	-----------	Moderate
[38]	MNIST	CNN-ML-ELM-AE	-------	99.35	1113.09	-------	Intermediate
		ELM-HLRF	-------	98.43	27.8	-------	Intermediate
		PCANet-ELM-AE	-------	99.02	------	-------	Intermediate
		CNN-ELM	-------	96.80	8.22	-------	Intermediate
		ELM-CNN	-------	99.16	157.08	-------	Intermediate
		CNN-ELM	-------	99.33	-----	-------	Intermediate
		R2ELM-LRF	-------	99.21	2658.36	-------	Intermediate
		ELMAENet	-------	99.46	-----	-------	Intermediate
		ELM-ARF	-------	98.95	265	-------	Intermediate
		ELM-MAERF	-------	99.43	204	-------	Intermediate
[39]	MNIST	ML-ELM	-------	99.0	281.71	Sigmoidal	Intermediate
		HELM	-------	98.99	101.39	Sigmoidal	Intermediate
		EH-ELMU	-------	99.01	78.23	Uniform distribution	Intermediate
		EH-ELMG	-------	99.0	78.23	Gaussian	Intermediate