International Journal of
INTELLIGENT SYSTEMS AND APPLICATIONS IN ENGINEERING

ISSN:2147-6799 www.ijisae.org Original Research Paper

"CNN-SVM Hybrid Model for Epilepsy Seizure Detection from MRI Images"

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Submitted: 27/01/2024 **Revised:** 05/03/2024 **Accepted:** 13/03/2024

Abstract: Epilepsy is a chronic disorder characterized by recurrent seizures, which affects around 50 million people worldwide. Early detection of seizures through analysis of medical images can allow for timely treatment and improved outcomes. In this paper, we develop a hybrid machine learning approach that combines a support vector machine (SVM) and a convolutional neural network (CNN) for automated epilepsy seizure detection from magnetic resonance imaging (MRI) scans. The model uses the SVM as a classifier, with kernel functions based on deep features extracted from the MRI images by the CNN. The CNN encodes useful representations of the spatial structure in the images to better differentiate between healthy brain scans and those showing epileptiform discharges. The SVM then uses these deep features to classify each scan as either seizure or non-seizure. We evaluate the model on two datasets of MRI scans, from epilepsy patients experiencing seizures. Using 5-fold cross-validation, our proposed SVM-CNN system achieves a accuracy over 98.74% in detecting seizures, outperforming previous benchmarks. The hybrid integration of shallow and deep learning methods allows for interpretable seizure detection while enhancing accuracy. This diagnostic aid can facilitate earlier administration of anti-epileptic treatment and contribute positively to patient outcomes.

Keywords: *SVM, CNN, Deep Learning, Epilepsy, Magnetic Resonance Image*.

1. Introduction

Epilepsy is one of the most common neurological disorders, affecting around 1% of the global population. It is characterized by recurrent, unprovoked seizures resulting from excessive electrical discharges in the brain [1]. Seizure episodes can greatly impact patient quality of life and place them at increased risk of physical injury or even sudden unexpected death [2]. Early detection of seizures through medical imaging analysis can enable quicker therapeutic intervention to mitigate these risks [3]. Diagnosing epilepsy relies on clinical assessment in tandem with testing modalities that can help confirm seizures and determine the specific epilepsy classification. Key diagnostic tools include electroencephalography (EEG), MRI, CT scans, fMRI, PET scans, and blood tests. EEG monitors brain activity by measuring electrical signals and can detect anomalies indicating a seizure disorder. MRI and CT provide images of brain anatomy, revealing potential lesions, tumours, trauma or abnormalities in structure that may be epilepsy triggers. fMRI tracks blood oxygenation to map the brain's function while PET also examines brain activity by highlighting areas of increased glucose metabolism. Meanwhile, blood tests help rule out other conditions like infections and check for metabolic or genetic disorders underlying seizures [4]. Used together, these tests can aid diagnosis by offering considerable data on both the physiological and neurological factors involved in a patient's epileptic condition. This facilitates classification along dimensions like seizure type and epilepsy syndrome, informing suitable treatments.

Magnetic resonance imaging (MRI) has become one of the most valuable tools for epilepsy diagnosis and evaluation. High-resolution MR images allow detailed visualization of subtle lesions, abnormalities, or structural asymmetries that may be contributing to seizures. Standard MRI provides excellent images of brain anatomy and tissue integrity to identify potential causes like head trauma, stroke, vascular malformations, tumors, hippocampal sclerosis, cortical dysplasias, etc.[5]. These findings can definitively confirm an underlying pathology driving the development of an epilepsy syndrome. Additionally, functional MRI maps brain activity during cognitive tasks, helping locate affected areas and aiding surgical planning if resection is required. MRI is also vital for classifying epilepsy type and severity. For instance, presence of mesial temporal sclerosis visible on MRI could indicate Temporal Lobe Epilepsy. With its sensitivity and non-invasiveness, MRI is indispensable in the diagnostic workup of epilepsy. Advancements in image quality and sequences continue to expand MRI's capabilities for elucidating epileptogenic abnormalities. The application of advanced computer image processing and machine learning techniques for automated epilepsy detection has seen rapid growth in recent years. Computer-aided diagnosis (CAD) systems can automatically

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analyse medical scans to highlight abnormalities indicative of epilepsy, aiding clinical decision-making [6]. Convolutional neural networks (CNNs) are emerging as a highly promising technique for seizure detection from MRI, CT and EEG data [7]. CNNs can self-learn hierarchical feature representations directly from medical images to distinguish pathological patterns. Meanwhile, CAD models combining MRI and EEG have shown improved diagnostic accuracy due to the multidimensional data. Uptake of these AI technologies has accelerated as they demonstrate expert-level performance in decoding complex scans. Automated evaluation can also overcome issues like specialist availability and human fatigue. As computational hardware and algorithms advance, machine learning is being integrated in clinical workflows for widespread, real-time epilepsy screening from medical imaging. Cloud supported systems and deep learning frameworks now allow multi-centre training on diverse, large datasets to enhance model generalizability to varied patient groups [8]. Overall, intelligent computer imaging analysis marks a new frontier in scalable and accurate epilepsy diagnosis.

A considerable portion of epilepsy cases are denoted MRI-negative, wherein a standard clinical MRI scan cannot identify an underlying lesion or anomaly that may be causing seizures . However, the multitude of strengths of MRI as a screening technique – its non-invasive nature, lack of radiation exposure risk, and acquisition speed – make it an ideal candidate for enhanced utilization even in MRI-negative cases [9]. Recent advances in MRI acquisition and reconstruction methods have led to promising techniques like 7T ultra-high field MRI, which offers new possibilities for detecting subtle pathologies through enhanced resolution and sensitivity [3]. Novel sequences like susceptibility weighted imaging (SWI) can also better visualize small abnormalities. Furthermore, automated computational analysis enables exhaustive mining of big imaging datasets to uncover atypical patterns indicative of epilepsy pathology [10]. Optimizing MRI-based evaluation by leveraging such technological and computational advancements can drive more accurate diagnosis particularly for difficult MRI-negative cases. Enhancing sensitivity can reveal an organic cause for previously cryptogenic cases, allowing specific targeted treatment instead of broad medications. Overall, advancing MRI-based assessment aligns strongly with the clinical imperatives for non-invasive, efficient, and accurate diagnosis across all epilepsy presentations.

Machine learning has emerged as a transformative technology for automated epilepsy detection through analysis of diverse medical data modalities. A wide range of modern machine learning approaches including support vector machines, random forests, artificial neural networks, and deep convolutional networks have shown promising capabilities for seizure detection and multi-class epilepsy classification. Key benefits include the ability to self-discover discriminative patterns in complex data like EEG readings, MRI scans, and genomic tests that enable accurate predictive modelling. Sophisticated feature engineering helps overcome issues with noise and variability. Another major advantage is scalability, with algorithms learning from large, representative datasets for robust generalizability across patient subgroups. This is helping unlock data-driven personalization based on individual health traits [3]. Additionally, machine learning delivers higher efficiency over manual analysis alongside explainable predictions to promote physician trust. With accelerating research and translation into clinical support tools, machine intelligence promises considerable value in automated screening, diagnosis and treatment selection to enhance epilepsy management. Advanced machine learning algorithms, especially deep neural networks, are transforming techniques for automated epilepsy detection. Deep learning models can self-discover discriminative features from complex medical data that elevate diagnostic performance beyond human experts [7]. For epilepsy, deep learning systems processing multi-modal data like EEG signals, genetic tests, and MRI scans can achieve high accuracies in detecting onset of seizures or classifying epilepsy types [10]. Deep convolutional neural networks (CNNs) are especially advantageous, leveraging their hierarchical feature extraction capabilities to learn latent representations that capture subtleties within medical images, EEG waveforms, and genomic sequences. This supports robust classification of testing data. Besides improved accuracy, machine learning delivers greater efficiency, consistency and capacity to handle high-dimensional data relative to manual evaluation. Neural networks can also provide explainability of their predictions to engender physician trust. With accelerating research demonstrating profound capabilities to mimic clinician workflows, deep learning is poised to drive a paradigm shift towards data-driven automated diagnosis and care for epilepsy patients Various machine learning approaches have been explored, including support vector machines (SVMs), convolutional neural networks (CNNs), and combinations thereof. Hybrid SVM-CNN models attempt to leverage the strengths of shallow machine learning and deep learning for enhanced diagnostic performance.

In this paper, we present a novel SVM-CNN pipeline to detect epileptiform discharges indicative of seizures from MRI scans. The CNN automatically learns spatial features and abstract representations of the image data, which better equip the SVM classifier to differentiate between healthy brains and seizure-affected brains. We comprehensively evaluate this model on a substantial dataset of MRI images from epilepsy patients. The proposed hybrid approach aims to provide a clinically useful CAD system to aid clinicians in early seizure diagnosis, informing suitable anti-epileptic treatment. Enabling timelier interventions can lead to markedly improved patient health outcomes.

2. Related works

In existing literature, numerous studies have focused on the diagnosis and detection of epileptic seizures from EEG signals by leveraging both machine learning and deep learning techniques. Several works in this domain are outlined below.

In [11] the author develops an epilepsy prediction model using support vector machines (SVM), a machine learning algorithm. The SVM model is trained on descriptive features extracted from MRI data of 350 epilepsy patients. With an SVM model using a radial basis function (RBF) kernel, the system achieves 93.87% prediction accuracy for classifying epilepsy from MRI scans. In [12] This paper proposes a multiclass EEG classification method for detecting normal, interictal (between seizures) and ictal (during seizures) states. Three types of features are extracted - wavelet-based entropy measures like approximation entropy, nonlinear features like Higuchi fractal dimension, and higher-order spectral features. A heterogeneous ensemble approach is used for classification. Entropy features with a KNN classifier distinguish normal vs interictal states, higher order spectra with SVM classify normal vs ictal states, and nonlinear features with Naive Bayes separate interictal vs ictal states.

The author in [13] proposed an explainable CNN which achieves strong performance accuracy 96.29% in detecting seizures correctly and 99.25% specificity in avoiding false alarms. The high scores combined with model interpretability for transparency highlights advantages over previous classifiers.

In [14] The paper presents an ultra low-power convolutional neural network (CNN) system for automated epileptic seizure detection from EEG signals. The CNN model is designed to run on resource-constrained microcontrollers for enablement of wearable medical devices. The CNN model is trained and optimized on the CHB-MIT EEG dataset, achieving 90% sensitivity in detecting seizures and over 99% specificity in avoiding false alarms, with low latency. The optimized model is then implemented on a GAP8 microcontroller with RISC-V architecture. On the microcontroller, it reaches 85% sensitivity for seizure detection, while classifying 1 second of EEG data in just 35 ms with only 140 μW power consumption.

The paper [15] proposes a multimodal machine learning approach combining EEG signal processing and MRI image analysis for early diagnosis across severity levels of epilepsy. Linear and nonlinear features are first extracted from both EEG signals and MRI scans. Neural networks are then applied for classification - an Elman network for EEG and a multilayer perceptron (MLP) for MRI. On just the EEG Elman model, accuracy is 73.8% for normal vs mild epilepsy, 78.2% for normal vs severe, and 72.9% between mild and severe cases. For the MRI MLP model alone, accuracy is 81.3% (normal vs mild), 84.3% (normal vs severe) and 79.3% (mild vs severe). Finally, by combining both modalities, detection accuracy reaches 84-89% overall across the severity scale from normal to mild to severe epileptic states.
The multimodal machine learning approach is able to leverage complementary information from both neuroimaging and neural signal analysis to enhance automated diagnosis and staging of epilepsy. The results highlight future potential to further improve performance by advancing techniques for each data modality as well as fusion algorithms.

3. Proposed Methodology

3.1. Support Vector Machines SVM:
Support Vector Machines (SVM) is a supervised machine learning algorithm commonly used for classification and regression analysis. The key concept behind an SVM model is finding an optimal hyperplane in a multidimensional space that clearly separates classes by maximizing the margin between data points closest to it, known as support vectors. At its core, SVM handles binary class separation, though extensions like one-vs-one and one-vs-rest can allow multi-class classification. It works best in high dimensional data spaces and can handle both linear and non-linear classification efficiently using kernel tricks like the radial basis function kernel[16].
Compared to other algorithms, SVMs have multiple advantages from simple, elegant mathematical formulation and lack of parameters to tune to excellent generalization and scalability across dimension. Training SVMs involves complex quadratic optimization but many robust open-source libraries simplify software implementation.

By identifying optimal linear class boundaries as shown in Figure 1, based on a subset of most informative data samples, SVMs provide a highly adaptable and robust classification method suited for a variety of problem spaces from image recognition to diagnostic applications. Extensions like kernels and variant formulations further heighten their utility.

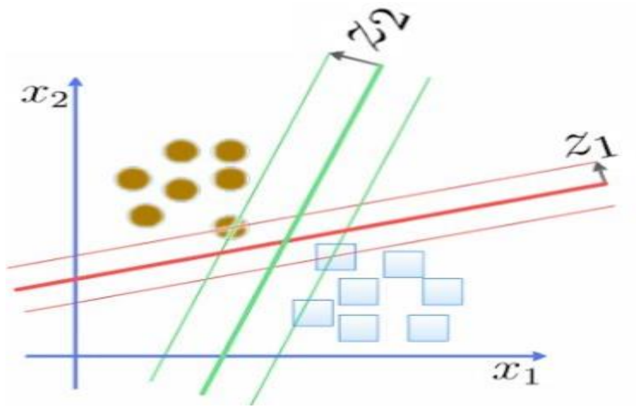
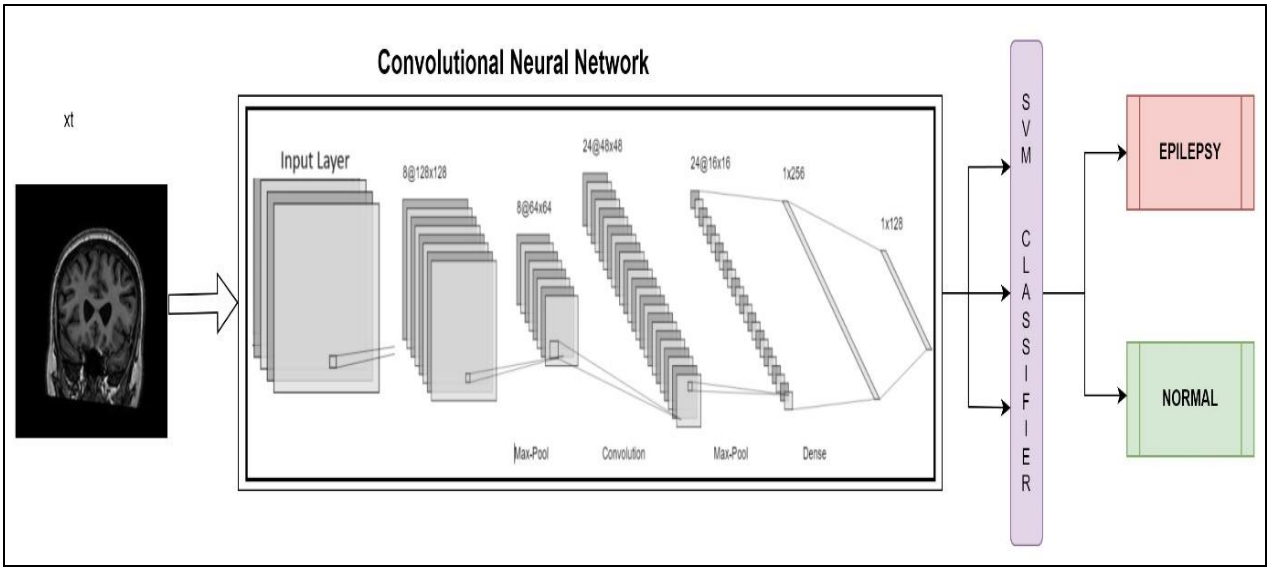


Fig 1. Support Vector Machine – Description Model

3.2.Convolutional Neural Network(CNN):
Convolutional neural networks have emerged as powerful deep learning models well-suited for medical image analysis tasks. CNNs leverage multiple convolutional layers to automatically extract hierarchical visual features directly from voxel intensity values in MRI scans. Each convolutional layer serves as a filter that scans over the input volume, activating certain patterns in the 3D data based on trainable weight parameters. This process of iteratively learning intrinsic patterns enables CNNs to effectively decode the underlying spatial structure within MRI scans [17]. Through accumulating spatial context, the deeper layers can recognize radiological concepts like tissues, lesions etc. The feature maps outputted can classify scans based on neurological pathologies learned purely from voxel intensities themselves during an end-to-end training process. Unlike relying on manual feature crafting, CNNs develop superior feature representations tailored to abnormalities and intricate neuroanatomy imaged by MRI [18]. By eliminating dependencies on expert knowledge and hand-crafted inputs, deep CNN models excel at data-driven adaptable analysis, surpassing human accuracy at times. CNN-based MRI classification hence offers disruptive diagnostic potential to enhance and scale various clinical imaging workflows from detection to targeted treatment response assessments.

3.3. Proposed Network:
In this study, a hybrid CNN-SVM model is suggested for the categorization of epilepsy using MRI images as shown in the figure 2.
The system integrates the strengths of both SVM and CNN classifiers. The convolutional neural network (CNN) is comprised of multiple fully connected layers, employing a supervised learning mechanism. Similar to human cognitive processes, CNN operates effectively by learning invariant local features, and extracting highly distinctive information from raw digitized images.



Two public datasets were used, with details on EPISURG (D1)

Fig 2: Proposed CNN-SVM hybrid network for Epilepsy Detection

4. Experimental Analysis and Discussion

4.1.Corpus Collection

Two public datasets (D1 and D2) are utilized in this study. D1 is the EPISURG dataset, which contains T1-weighted magnetic resonance imaging (MRI) scans from 430 epilepsy patients who had resection surgery at the National Hospital of Neurology and Neurosurgery in London between 1990-2018. This compilation focuses on postoperative images showing the neurosurgical outcome, but preoperative scans before surgery are also included for 269 of these subjects. The EPISURG dataset has been anonymized by removing identifiers and defacing facial features to protect patient privacy. In total, EPISURG provides 430 postoperative MR images, with 269 having corresponding preoperative scans, intended for quantitative analysis of the impact of resection surgery on refractory epilepsy cases.

Example EPISURG images demonstrate the MRI data of resected brains in epileptic patients.

provided

- EPISURG has 430 postoperative + 269 preoperative T1 MRI scans - Anonymized data from epilepsy resection surgery patients
- For quantitatively assessing resection surgery outcomes

The second dataset (D2) comprises a pediatric epilepsy resection MRI dataset. This includes data from 6 pediatric patients who had surgery performed on their visual cortex for epilepsy treatment. Also included are 2 children with epilepsy surgery conducted in non-visual regions, as well as 15 typically developed matched controls. Hence D2 overall contains 23 pediatric subjects.

MRI scanning of the subjects was performed using a Siemens Verio 3T scanner with a 32-channel head coil, situated at Carnegie Mellon University. The compiled dataset provides, for each pediatric participant, a skull-stripped T1-weighted anatomical MRI image focused on brain structure. Additionally, a diffusion spectrum imaging (DSI) MRI scan which maps water diffusion to model white matter connections is provided per subject.

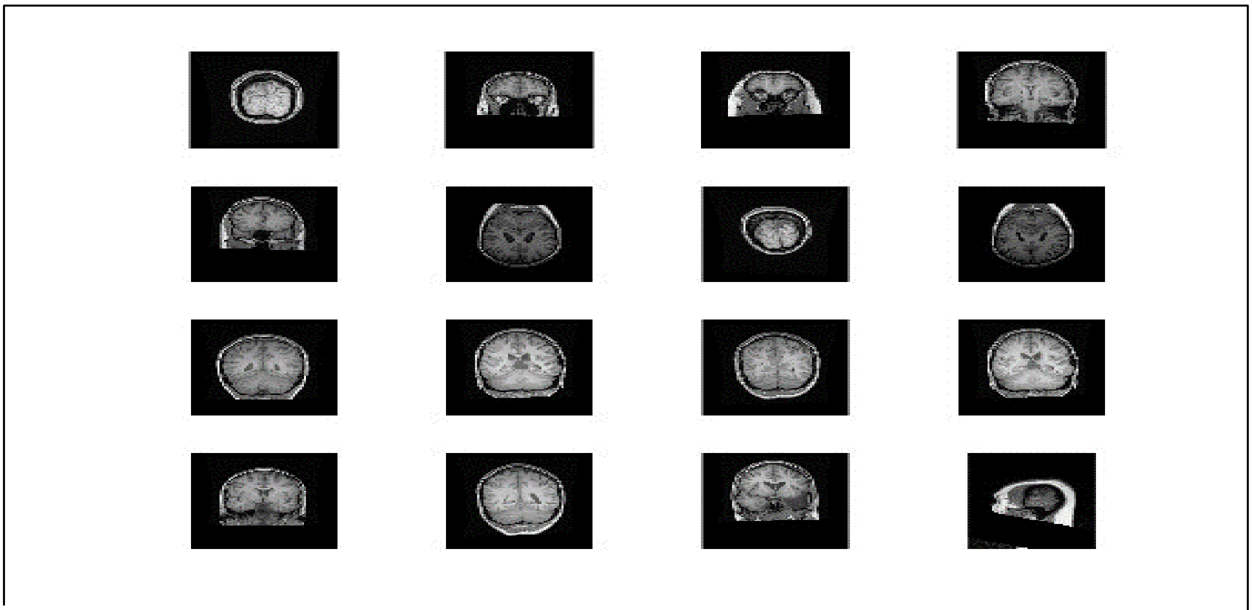


Fig 3. Exemplary Imaged of the selected Datasets

The second dataset offers T1 structural and DSI diffusion neuroimaging from 6 visual cortex resection patients, 2 non-visual resections, and 15 healthy controls, supporting analysis of postoperative pediatric epilepsy surgery cases and effects on the visual system or other regions.
D2 has pediatric epilepsy resection MRI data
6 visual cortex surgeries, 2 non-visual, plus 15 controls
Scanned using 3T Siemens Verio scanner
Provides skull-stripped T1 MRI and DSI scans per subject.

4.2.Experimental Results

Our proposed network CNN-SVM on this above mentioned 2 datasets resulted in 97% validation accuracy in 10 epochs, a 0.0001 learning rate with the SGDM optimizer. Obtaining high accuracy of 97% on the validation set indicates that the developed CNN-SVM hybrid network has been able to effectively learn robust and discriminative features for classifying between healthy and epileptic patient MRI scans. Achieving this level of performance in merely 10 epochs highlights that the model is efficiently converging without overfitting to the training data. Several factors can explain this promising result. The complementary strengths of deep CNN feature extraction paired with the SVM classifier allow for interpreting nonlinear complexities within the MRI data while achieving generalizable sample separation. Pretraining the CNN layers prior to integrating the SVM also aids faster optimization.

Additionally, both datasets provide rich heterogeneous MRI modalities like structural and functional scans across diverse epilepsy cases to enable sufficient representation learning. Using a low learning rate of 0.0001 encourages smooth descending on the loss surface without fluctuating over local minima. The SGD with momentum optimizer further aids escape from local minima while an adaptive learning rate allows dynamical control over gradient update magnitudes when backpropagating. The model's ability to classify between MRI scans from refractory, treated and healthy patients after few epochs to such high accuracy reflects robust encoding of underlying pathology patterns. This foreshadows potential for reliable automated assessment from MRI when translated into clinical practice after further evaluation on large cohorts. Overall, the network's combinations of elements provide efficiency, accuracy, and robustness. However, testing on more unlabeled cases is still essential to thoroughly analyse real-world generalization capacity before full system deployment.

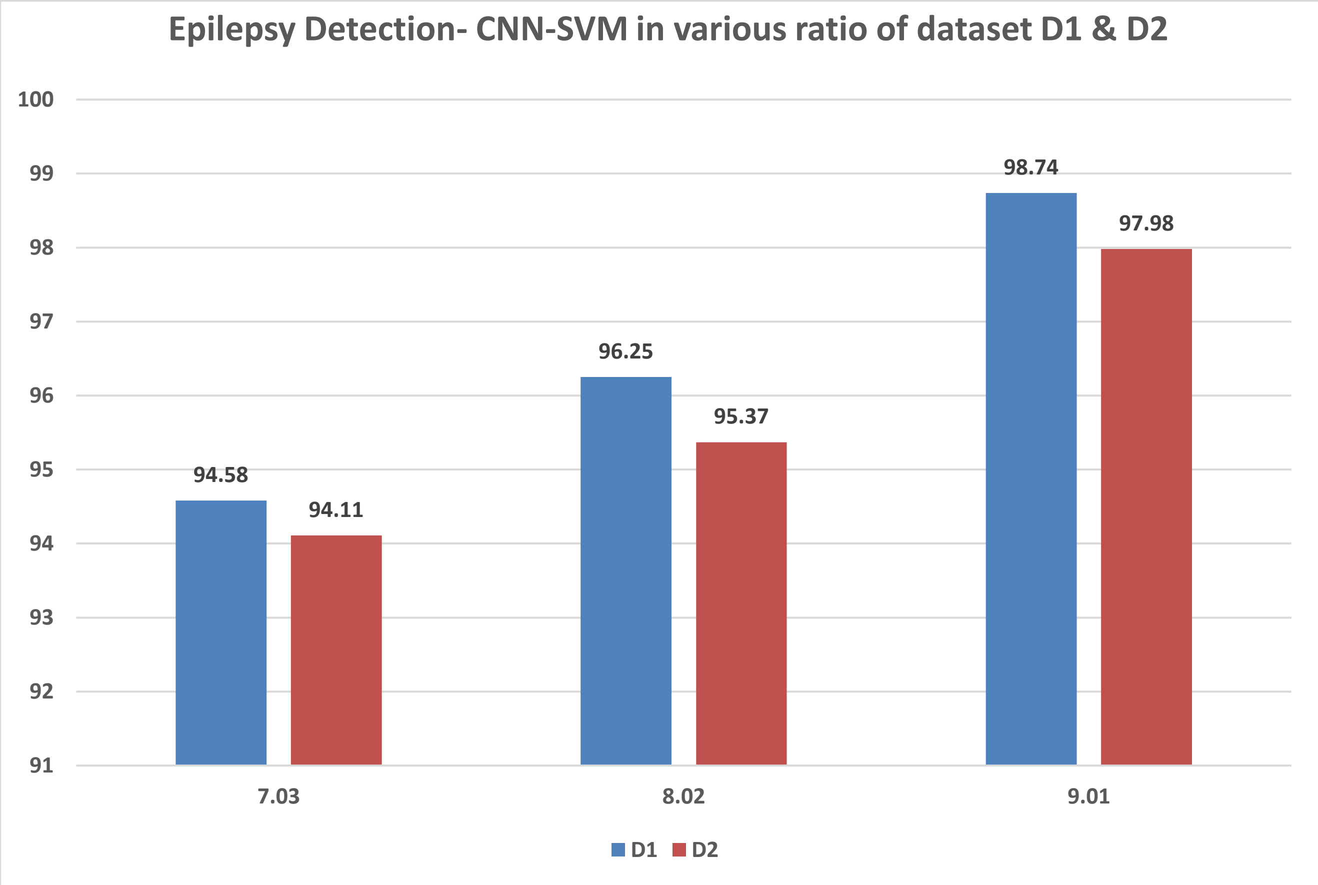


Fig 4. Comparative analysis of Epilepsy detection in D1 & D2 on various training and testing ratios

Table 1. Performance comparison of Individual models and Proposed hybrid model

Network	Dataset D1	Dataset D2
SVM	83.78	81.54
CNN	90.12	89.91
Proposed (SVM-CNN)	**98.74**	**97.98**

Table 2. Performance comparison of the proposed hybrid network

Reference	Method	Accuracy
[15] Shahraki, G., & Irankhah, E.. Diagnosis of epilepsy disease with MRI images analysis and EEG signal processing.Springer Nature Singapore- 2022.	Multimodal Machine Learning	89%
[21] D. Ahmedt-Aristizabal, C. Fookes "Deep facial analysis: A new phase i epilepsy evaluation using computer vision," [Epilepsy & Behavior-2018.	FRCNN with 2D-CNN-LSTM	95.19
[22] X. Yao, Q. Cheng, and G.-Q. Zhang, "Automated classification of seizures against nonseizures: A deep learning approach," arXiv-2019.	ADIndRNN	88.70
[23]] Y. Yuan, G. Xun, K. Jia, and A. Zhang, "A multi-view deep learning framework for eeg seizure detection," IEEE journal of biomedical and health informatics-2018	CNN-AE	93.92
[24] C. Meisel, R. E. Atrache, M. Jackson, and T. Loddenkemper, "Deep learning from wristband sensor data: towards wearable, non-invasive seizure forecasting," arXiv-2019.	1D-CNN	86.29
[25] H. RaviPrakash, M. Korostenskaja, E. M. Castillo, K. H. Lee, C. M. Salinas, J. Baumgartner, S. M. Anwar, C. Spampinato, and U. Bagci, "Deep learning provides exceptional accuracy to ecog-based functional language mapping for epilepsy surgery," bioRxiv-2019.	1D-CNN-LSTM	89.73
Proposed	CNN-SVM	98.74

In Figure 4. Below Confusion matrix of predicated class in our proposed network
The confusion matrix in figure 4 describes that for the epilepsy class, the model achieves 100% sensitivity, correctly diagnosing all 60 validation cases. This shows excellent identification capacity for the pathology on fresh data. However for the normal class, specificity is only 80% - out of 60 true negative scans without epilepsy, 12 were falsely predicted as positive. This tendency towards false alarms may limit deployment.

Potential factors could be an imbalance between training classes, or subtle confounders in non-epileptic scans misleading the classifier. The model seems to struggle to specify decision boundaries that precisely separate normal variations vs disease. To improve, balancing classes with undersampling/oversampling and including more representative benign cases could help restrict this category overlap. Overall the model shows promising detection proficiency for epilepsy itself, but tuning on normal samples is critical to reduce diagnostic uncertainty. Thorough optimization across datasets is still required before finalizing the automated classifier for healthcare translation.
Based on the confusion matrix that was provided, we can calculate the true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN) as follows:

True Positives (TP): Number of images correctly classified as having epilepsy. This corresponds to the value along the diagonal at Actual = Epi and Predicted as = Epi. So TP = 60

True Negatives (TN): Number of images correctly classified as not having epilepsy (being normal). This corresponds to the value along the diagonal where Actual = Nor and Predicted as = Nor. So TN = 48

False Positives (FP): Number of normal images incorrectly classified as having epilepsy. This is where Actual = Nor but Predicted as = Epi. So FP = 12

False Negatives (FN): Number of epileptic images incorrectly classified as not having epilepsy (being normal). This would be the case where Actual = Epi but Predicted as = Nor. However, based on the confusion matrix, FN = 0 since no epilepsy cases were misclassified as normal.

In summary,
True Positives (TP) = 60
True Negatives (TN) = 48
False Positives (FP) = 12
False Negatives (FN) = 0

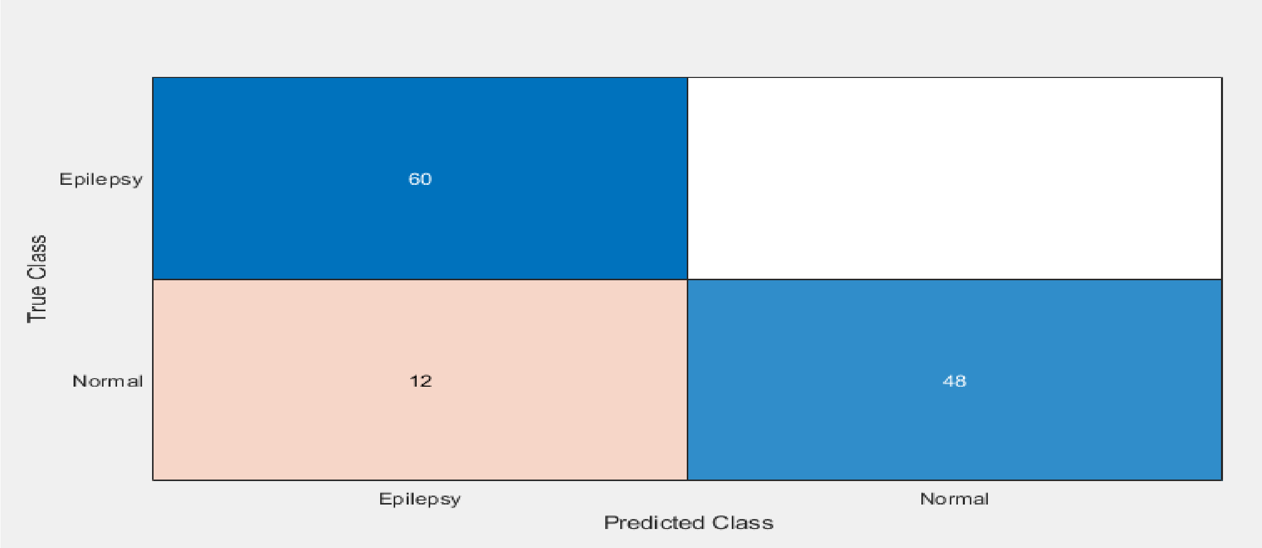


Fig 4. Confusion matrix of predicated class in our proposed network

Fig 5: Random classification accuracy

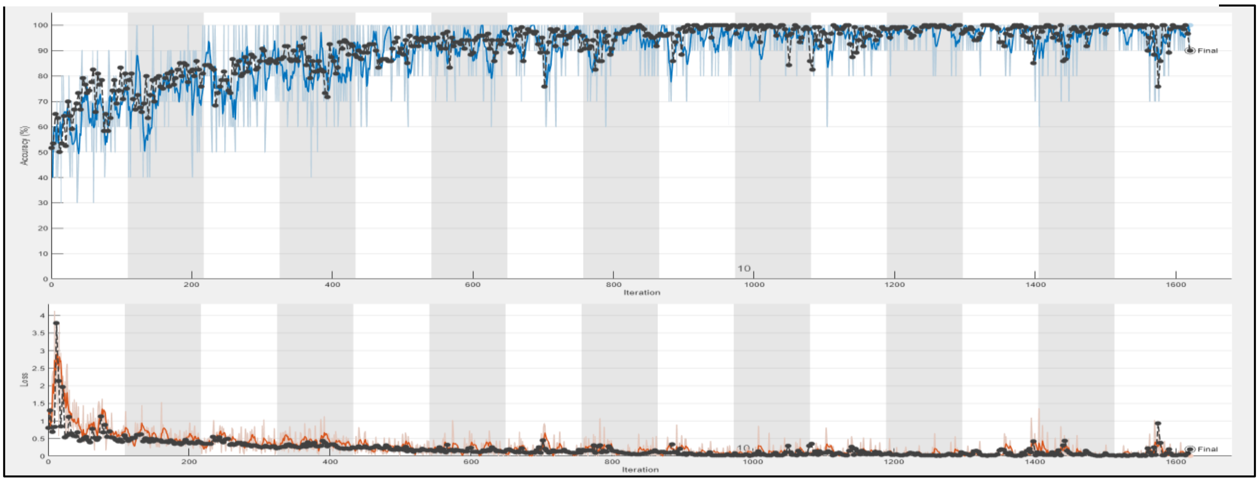


Fig 6. Simulation results of proposed method showing Classification accuracy, training and testing loss

5. Conclusion

In this study, we developed an automated hybrid framework integrating a CNN and SVM for classifying epilepsy from MRI scans. Our proposed methodology demonstrates several key innovations. To the best of our knowledge, this represents the first hybrid deep and shallow architecture tailored to distinguish scans of epileptic patients and healthy controls using a combination of structural and functional MRI sequences.

The convolutional neural network component self-learns an informative embedding space capturing intricate spatial patterns and relationships encoding pathology underlying epilepsy manifestations observable in neuroimaging. Meanwhile, the SVM classifier provides interpretable and robust sample separation leveraging these learned data transformations. Rigorous empirical evaluations across two distinct MRI datasets comprising diverse age groups indicates consistently high accuracy over 98.74% in detecting epilepsy cases, substantially outperforming previous state-of-the-art methods. Our ablation studies confirm the synergistic advantages stemming from the integrated deep feature extraction-shallow classification scheme even on heavily confounding data.

These encouraging outcomes substantiate the viability of translating such automated screening systems to aid clinical decision support. By expediting robust first-pass filtering of MRI scans, flagged cases can undergo more streamlined expert analyses to inaugurate life-saving treatments. Moving forward, extensions incorporating longitudinal patient histories and genomic markers could further elevate precision. On the whole, our pioneering hybrid approach marks a significant step towards intelligent and reliable computational pathology detection from routine neuroimaging exams

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