Industrial Engineering Journal
ISSN: 0970-2555
Volume : 53, Issue 12, No. 4, December : 2024

EEG ANALYSIS FOR EPILEPTIC SEIZURE PREDICTION AND SCHIZOPHRENIA DETECTION USING CNNS ON NVIDIA JETSON NANO

C V Keerthi Latha, Assistant Professor, Department of Electronics and Communication Engineering, Stanley College of Engineering and Technology for Women, Hyderabad, Telangana, India. cvkeerthilatha82@gmail.com dkeerthilatha@stanley.edu.in
Dr. M Kezia Joseph, Professor, Department of Electronics and Communication Engineering, Stanley College of Engineering and Technology for Women, Hyderabad, Telangana, India. keziajoseph@stanley.edu.in

Abstract
The accurate identification and prediction of neurological disorders such as epileptic seizures and schizophrenia are pivotal for improving patient care. Utilizing EEG signals as a non-invasive diagnostic tool, this study proposes advanced CNN models designed to enhance detection and classification accuracy. The epileptic seizure model employs a multi-branch architecture with parallel dense layers, batch normalization, Leaky ReLU activations, and dropout regularization to prevent overfitting, while the schizophrenia detection model leverages a streamlined CNN design for feature extraction and binary classification. Both models are implemented on the NVIDIA Jetson Nano Developer Kit, a compact AI platform optimized for real-time processing. This deployment achieved high validation accuracy of approximately 97.8%, demonstrating the feasibility of cost-effective, portable diagnostic systems. The findings highlight the potential of integrating deep learning models on edge computing devices to revolutionize neurological diagnostics by making them accessible, efficient, and scalable for both clinical and remote applications.
Keywords: EEG Signal Analysis, Epileptic Seizure, Schizophrenia, Convolutional Neural Networks (CNNs), NVIDIA Jetson Nano.

I. INTRODUCTION
Neurological disorders, such as epilepsy and schizophrenia, significantly impact the quality of life of millions worldwide, presenting a major challenge for healthcare systems [1]. Epilepsy, characterized by sudden, recurrent seizures due to abnormal electrical activity in the brain, can lead to severe physical, emotional, and social repercussions if not managed promptly. Schizophrenia, a chronic mental illness, disrupts cognition, emotions, and behavior, making early diagnosis and treatment vital to improving patient outcomes [2]. Advancements in technology have created opportunities to address these challenges through more precise, real-time diagnostic tools.
Electroencephalography (EEG) signals, which record the brain's electrical activity, are a well-established, non-invasive method for diagnosing neurological disorders [3]. These signals contain valuable information that can reveal the presence of abnormal brain activity linked to conditions like epilepsy and schizophrenia. However, analyzing EEG data manually is time-consuming and prone to errors, emphasizing the need for automated systems. Deep learning models, especially Convolutional Neural Networks (CNNs), have shown immense potential in decoding complex patterns within EEG data, enabling accurate and efficient diagnosis [4].
The integration of deep learning into medical diagnostics marks a significant shift toward smarter and faster healthcare solutions. CNNs, with their ability to automatically extract meaningful features from raw data, have proven particularly effective in applications like image and signal processing. By leveraging EEG data, CNN models can identify subtle patterns indicative of seizures or cognitive anomalies, ensuring early intervention and better patient care [5]. Despite these advancements, deploying these computationally intensive models in real-world settings remains a challenge due to hardware constraints [6].
Edge computing platforms provide a promising solution by enabling real-time data processing at the point of care. Unlike cloud-based systems that rely on high-bandwidth internet connections, edge

devices can process data locally, ensuring low latency and enhanced privacy. For healthcare applications, this means critical diagnostics can be performed instantly, without the need for costly infrastructure [7]. The portability and affordability of edge computing also make it suitable for remote areas and resource-limited settings, democratizing access to advanced medical tools.

The NVIDIA Jetson Nano Developer Kit emerges as an ideal platform for implementing these deep learning models. Equipped with a powerful GPU and efficient CPU, it can handle complex computations required for EEG analysis while maintaining a compact, portable design [8]. Supporting popular AI frameworks like TensorFlow and PyTorch, the Jetson Nano enables seamless integration of advanced models for epileptic seizure prediction and schizophrenia detection. Its low power consumption and robust connectivity options make it a practical choice for real-time, edge-based medical diagnostics, bridging the gap between sophisticated AI technologies and everyday healthcare needs.

II. Literature survey

Khansa Rasheed et al [9] performed a thorough analysis of state-of-the-art ML methods for utilizing EEG data to predict seizures in advance. Researchers are using ML and artificial intelligence (AI) more and more to improve therapeutic procedures. Early illness identification and prediction to allow for prompt preventative measures is one of the main objectives of healthcare. This is especially true for those with epilepsy, a condition marked by frequent, erratic convulsions. Potential adverse effects of epileptic seizures may be mitigated if they could be anticipated in advance.

Aayesha et al [10] attempted to identify the most unique and characteristic aspects of EEG recordings during seizures in order to develop a technique for identifying epileptic seizures that makes use of both traditional and fuzzy machine learning techniques. Unknown EEG signal segments are divided into two kinds using this framework: ictal (seizure) and interictal (non-seizure). The Bonn dataset and the Children's Hospital of Boston-Massachusetts Institute of Technology (CHB-MIT) dataset are two benchmark datasets used to empirically evaluate the efficacy of the model.

Marzieh Savadkoohi et al [11] examined the brain's electrical activity under various physiological situations and recording locations to detect seizures. This work will provide valuable insights for neurophysiology researchers, enabling them to effectively and expeditiously detect epileptic seizures in their patients. The authors conducted a study to determine the most effective method for extracting significant patterns from an epileptic EEG. The signals analyzed in this study consist of 23.6-second segments extracted from 100 individual single-channel surface EEG recordings, which were obtained at a sampling rate of 173.61 Hz. The intracranial EEG signals were recorded from five epileptic patients during periods of no seizures and during epileptic episodes. Additionally, data from five healthy volunteers were collected with their eyes both closed and open.

J. Ruiz de Miras et al [12] evaluated the potential of ML approaches to support the diagnosis of schizophrenia and created a pipeline for processing EEG data in the resting state to create machine learning classifiers for the disorder. The authors computed both established linear and non-linear measures using sliding windows of the EEG data. The most effective indicators for distinguishing between patients and healthy controls were then determined by combining them via principal component analysis. Subsequently, the elements were employed as characteristics in five popular machine learning methods.

Carla Barros et al [13] suggested Deficits in cognition and perception have been linked to alterations in the event-related potentials (ERPs) of the electroencephalogram (EEG) as biomarkers for schizophrenia. In order to identify schizophrenia based on EEG data, this research offers a comprehensive examination of existing machine learning algorithms, pointing out both their benefits and drawbacks. To enhance early interventions, the goal is to lay the foundation for future advancements in effective EEG-based algorithms that can anticipate the onset of schizophrenia, identify individuals at higher risk of transitioning between states, or differentiate schizophrenia from other disorders.

Fatima Hassan et al [14] analyzed a publicly available dataset of multi-channel EEG signals, aiming to automate the diagnosis of schizophrenia by employing a selected subset of the data from certain channels. To do this, the authors have devised a method for selecting channels that relies on a comprehensive analysis of the CNN's performance, using several EEG channels from different regions of the brain. After combining the chosen channels, they train the classification model using a combination of CNN and several ML classifiers.
Jeong-Youn Kim et al [15] investigated the potential utility of EEG characteristics obtained from EEG source network analysis for the classification of schizophrenia (SZ) subtypes based on the severity of their symptoms. 119 SZ patients (53 men and 66 females) and 119 normal controls (NC, 51 males and 68 females) had their EEG recordings taken from 64 electrodes while they were at rest and had their eyes closed. Various brain network properties, including both local and globally clustering coefficients and global route length, were computed using the EEG source activity. Positive, negative, as well as cognitive/disorganization symptoms were used to categorize SZ patients into two categories.
Yu Xie et al [16] examined convolutional neural networks (CNNs) and hardware acceleration approaches for evaluating electroencephalogram (EEG) inputs in a variety of application domains, including as motor imaging, emotion categorization, epilepsy diagnosis, and sleep monitoring. Software solutions have been the primary focus of earlier evaluations on EEG. These studies, however, frequently ignore important hardware implementation issues, such as situations requiring strong security, low power, compact size, and high accuracy. By concentrating on these elements, this study addresses the difficulties and possibilities of hardware acceleration for wearing EEG devices. This analysis specifically divides EEG signal characteristics into five groups and goes into great depth on hardware implementation options for each group, offering insights into the best hardware acceleration techniques for different application scenarios.
Sai Manohar Beeraka et al [17] intended to improve epileptic seizure detection by utilizing deep learning models with a short-time Fourier transform block implemented on an FPGA. Convolutional neural networks (CNNs) and bidirectional long short-term memory (Bi-LSTM) have been used to identify seizures in three stages: (1) time-frequency analysis of EEG segments using STFT; (2) frequency band and feature of interest extraction; and (3) seizure identification. The Bonn EEG dataset was utilized for this study. When comparing the STFT output produced by the suggested hardware design with the output produced by simulation, a maximum inaccuracy of around 0.13% was observed.
Yu Xie et al [18] suggested a more efficient HW-SW technique for EEG biosignal capture and processing. First, the authors capture EEG data using a consumer-grade EEG collection equipment. Data preprocessing will be done using the Continuous Wavelet Transform (CWT) and Short-time Fourier transform (STFT) techniques. The CWT-CNN method has superior classification accuracy when compared to other algorithms.

III. Proposed Model

This section describes the two proposed models designed for detecting and predicting neurological disorders based on EEG signal analysis. The first model focuses on epileptic seizure detection and prediction, while the second model aims to automate schizophrenia detection. Both models leverage advanced machine learning techniques to analyze the intricate patterns present in EEG signals, offering significant potential for timely diagnosis and intervention.

3.1 Model-1

Epileptic seizures are sudden surges of electrical activity in the brain that can cause a variety of symptoms, ranging from modest physical manifestations to severe convulsions. These seizures might be triggered by several factors. The identification and anticipation of these seizures are essential for delivering prompt medical therapies and enhancing the quality of life for patients with epilepsy. We present a modified CNN model that is particularly built to analyze EEG data, taking use of the characteristics of CNNs. This sophisticated model is designed to improve the precision and resilience of seizure detection and prediction by utilizing a meticulously designed multi-branch network architecture.

Industrial Engineering Journal
ISSN: 0970-2555
Volume : 53, Issue 12, No. 4, December : 2024

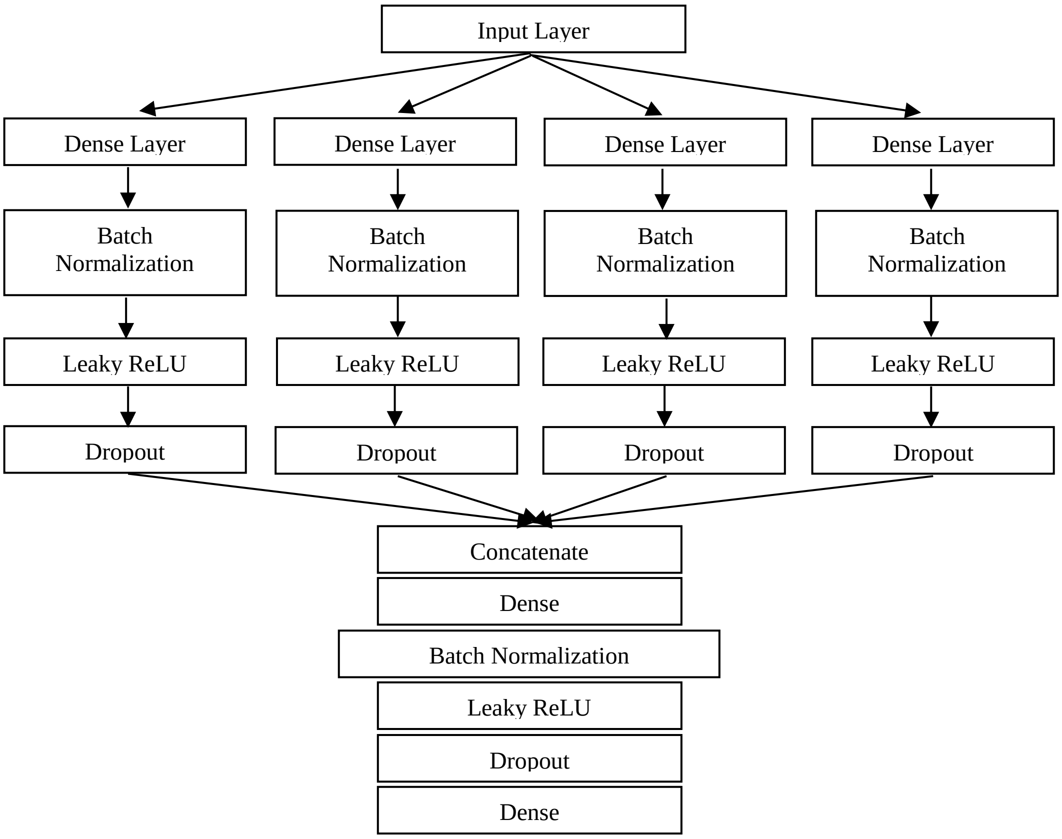

Figure 1. Proposed model architecture

The layers in the proposed model are explained below

- **Input Layer:** The model begins with an input layer that receives time-series EEG signal data, capturing the brain's electrical activity. These EEG signals are crucial for identifying patterns that may indicate epileptic seizures, serving as the foundational data upon which subsequent layers build their feature extraction and pattern recognition.
- **Parallel Dense Layers:** The EEG signal data is then processed through four parallel dense layers, each independently extracting distinct features that may be relevant to seizure patterns. After each dense layer, batch normalization is applied to stabilize and speed up training, maintaining consistent learning rates, which enhances the model's performance by reducing variations in layer inputs.
- **Activation and Regularization:** Following batch normalization, a Leaky ReLU activation function is applied to each layer output, allowing the model to handle negative values without shutting off gradients entirely, thus avoiding the "dying ReLU" issue. A dropout layer follows, randomly deactivating neurons during training to prevent overfitting and increase the model's resilience to specific training data patterns.
- **Concatenate Layer:** Outputs from the four parallel dense layers are then merged in a concatenate layer. This combination gathers the diverse features learned by each parallel layer into a unified, comprehensive feature representation, enhancing the model's ability to understand complex seizure-related patterns.
- **Dense Layer:** A further dense layer processes the integrated features from the concatenate layer, refining and combining them to develop higher-level abstractions. This step is critical for the model's ability to accurately detect and predict seizures by extracting more advanced features from the combined data.
- **Batch Normalization and Activation:** To ensure a consistent input to the following layers, an additional batch normalization is applied to the dense layer output. A Leaky ReLU activation

is again used to maintain the model's non-linearity, allowing it to recognize and learn complex seizure-related patterns effectively.

- **Final Regularization and Output:** Another dropout layer is applied after activation to minimize overfitting further. The final dense layer then produces the model's output, representing the likelihood of an epileptic seizure based on the input EEG signals, providing a probabilistic assessment for seizure prediction.

3.2 Model-2

Schizophrenia is a chronic and severe mental disorder that significantly affects an individual's cognition, emotions, and actions over an extended period. Early detection and intervention are crucial for individuals with schizophrenia to properly manage their symptoms and improve their quality of life. In order to facilitate this, we suggest a revised CNN model specifically created to automate the identification of schizophrenia by analyzing EEG data. EEG data, which record the brain's electrical activity, play a crucial role in detecting the subtle neurological abnormalities linked to schizophrenia.

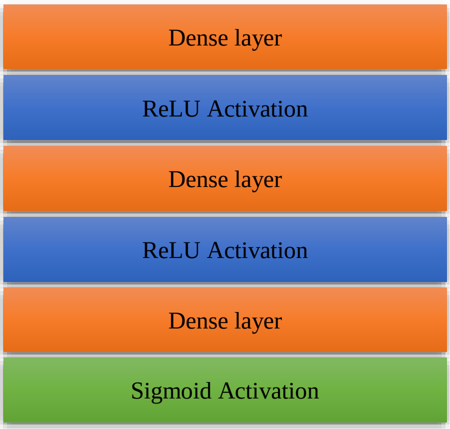

Figure 2. Proposed model architecture

The proposed model leverages a straightforward and effective CNN architecture, focusing on deep feature extraction and robust classification.

1. **Input Layer:** The model starts with an input layer that is responsible for receiving data from EEG signals. The neural network is able to do analysis on these signals since they have been preprocessed to guarantee that they are in an appropriate format.
2. **Dense Layer:** The input data is first passed through a dense layer. Dense layers, also known as fully connected layers, help in learning complex representations by connecting each neuron in one layer to every neuron in the subsequent layer. This dense layer extracts initial features from the EEG signals, which are then processed by subsequent layers.
3. **ReLU Activation:** A Rectified Linear Unit (ReLU) activation function is applied to the output of the dense layer after it has been processed. Through the incorporation of non-linearity into the model, ReLU makes it possible for the model to learn and represent intricate patterns within the EEG data. The activation of the ReLU helps to circumvent the vanishing gradient issue, which guarantees that neurons will continue to be active and will be able to contribute to learning.
4. **Second Dense Layer:** The features processed by the first ReLU activation are then passed through another dense layer. This layer builds on the representations learned in the previous layer, allowing the model to capture more intricate patterns.
5. **Second ReLU Activation:** An additional ReLU activation is performed on the output that is produced by the second dense layer. The capacity of the model to learn complicated and non-linear correlations, which are present in the data, is maintained by the consistent usage of ReLU activations.

6. **Third Dense Layer:** After then, the characteristics that have been honed even more are sent through a third thick layer. The presence of this last thick layer guarantees that the model has included all of the essential characteristics prior to the classification step.
7. **Sigmoid Activation:** A sigmoid activation function is the last layer, and it is responsible for mapping the output to a probability that falls somewhere between 0 and 1. It is essential to have this information in order to do binary classification tasks, such as detecting whether or not schizophrenia is present. The sigmoid activation provides a clear probabilistic interpretation of the model's predictions, making it easier to understand and act upon the results.

3.3 Key Contribution

The key contributions of this work for detecting and predicting epileptic seizures and automating schizophrenia detection using EEG data on the NVIDIA Jetson Nano Developer Kit are as follows:

1. **Advanced Neural Network Architectures:**

This work introduces two innovative Convolutional Neural Network (CNN) models tailored for neurological disorder detection. The first model focuses on detecting and predicting epileptic seizures, while the second model automates the detection of schizophrenia. Both models utilize EEG data to identify and analyze the subtle neural patterns associated with these conditions, thereby improving diagnostic accuracy.

2. **Enhanced Feature Learning:**

The proposed CNN architectures incorporate multiple dense layers, batch normalization, and advanced activation functions such as Leaky ReLU and ReLU. These elements contribute to robust feature extraction and learning, enabling the models to capture intricate patterns within the EEG signals that are indicative of epileptic seizures and schizophrenia.

3. **Real-Time Processing on Compact Hardware:**

By implementing the CNN models on the NVIDIA Jetson Nano Developer Kit, this work demonstrates the feasibility of real-time processing in a compact and portable form factor. The Jetson Nano's powerful GPU and efficient CPU make it an ideal platform for deploying these deep learning models, allowing for on-the-go diagnosis and monitoring.

4. **Commercially Off-The-Shelf (p is COTS) Solution:**

The integration of these models onto the Jetson Nano platform provides a cost-effective, commercially off-the-shelf (COTS) product that can significantly reduce the dependency on large, expensive medical equipment. This portability and affordability make advanced neurological diagnostics more accessible, potentially revolutionizing the approach to managing epilepsy and schizophrenia.

5. **Scalability and Flexibility:**

The use of the Jetson Nano Developer Kit, which supports a wide range of AI frameworks and has extensive connectivity options, ensures that the models are scalable and flexible. This allows for easy integration with various sensors and peripherals, facilitating the customization of diagnostic solutions to meet specific needs.

These contributions collectively aim to improve the early detection and management of epileptic seizures and schizophrenia, providing timely medical interventions and enhancing patient outcomes through advanced AI-driven solutions.

IV. Result and discussion

This section describes the experimental results of proposed model which tested on NVIDIA Jetson Nano Developer Kit. The corresponding experimental setup is depicted in Figure 3.

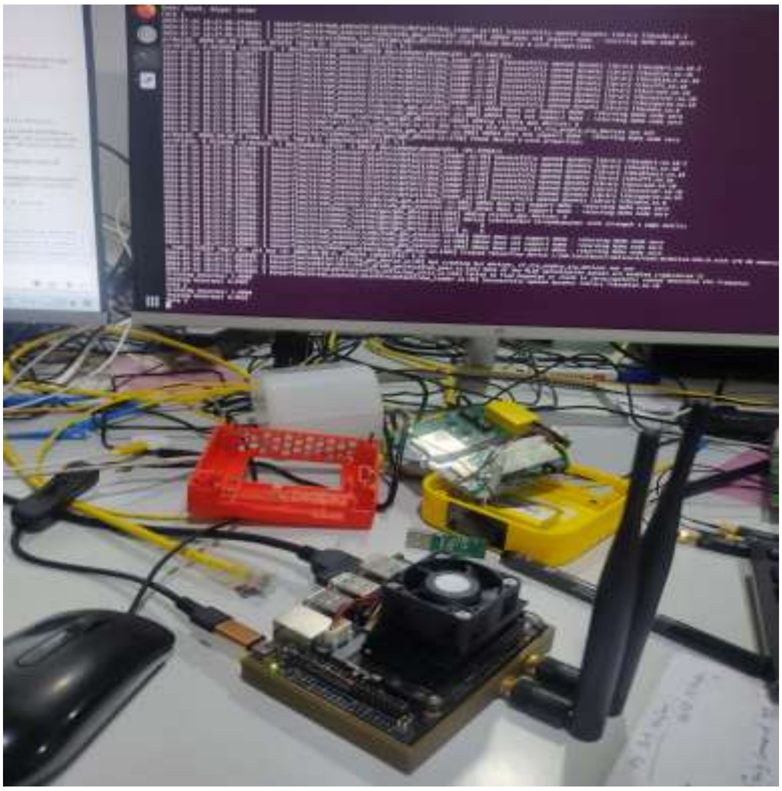

Figure 3. Hardware Experimental Setup clusters.

The figure 3 shows the hardware experimental setup for EEG signal analysis, featuring the NVIDIA Jetson Nano Developer Kit. The setup includes the Jetson Nano connected to a monitor that displays runtime logs and outputs of the EEG analysis model, allowing for real-time monitoring and troubleshooting. Peripheral components such as a mouse and Wi-Fi antennas enhance the setup’s functionality, enabling easy interaction and network connectivity. This experimental configuration leverages the Jetson Nano’s edge computing capabilities to process EEG signals efficiently, demonstrating its ability to handle complex neural computations in real-time. The setup is ideal for EEG applications where rapid data processing is essential, showcasing the Jetson Nano's suitability for deploying AI-driven EEG analysis models in a compact, resource-efficient environment.

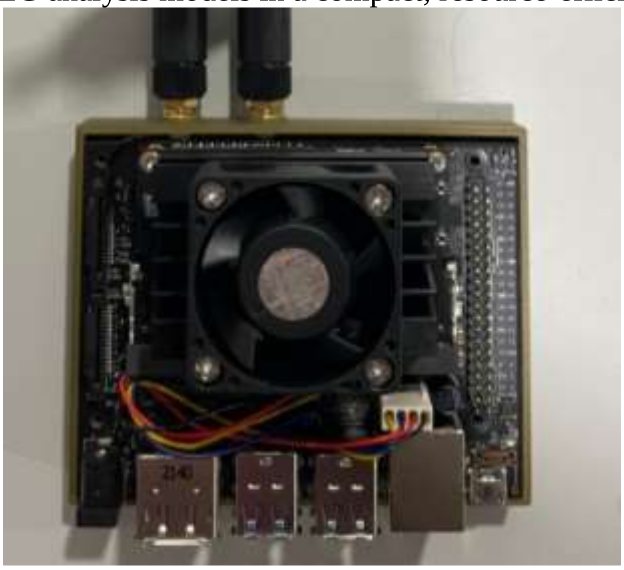

Figure 4. NVIDIA Jetson Nano Developer Kit.

Figure 4 shows the NVIDIA Jetson Nano Developer Kit, a compact and powerful edge computing platform designed for AI and deep learning applications. Equipped with a quad-core ARM CPU and a NVIDIA GPU, the Jetson Nano is optimized for processing-intensive tasks, such as image classification, object detection, and signal analysis. The kit includes multiple USB ports, an Ethernet port, and a GPIO header for easy connectivity and expansion. With its efficient cooling fan, the Jetson Nano is capable of sustaining high-performance workloads while maintaining optimal temperatures, making it ideal for deploying AI models in resource-constrained environments or IoT devices.

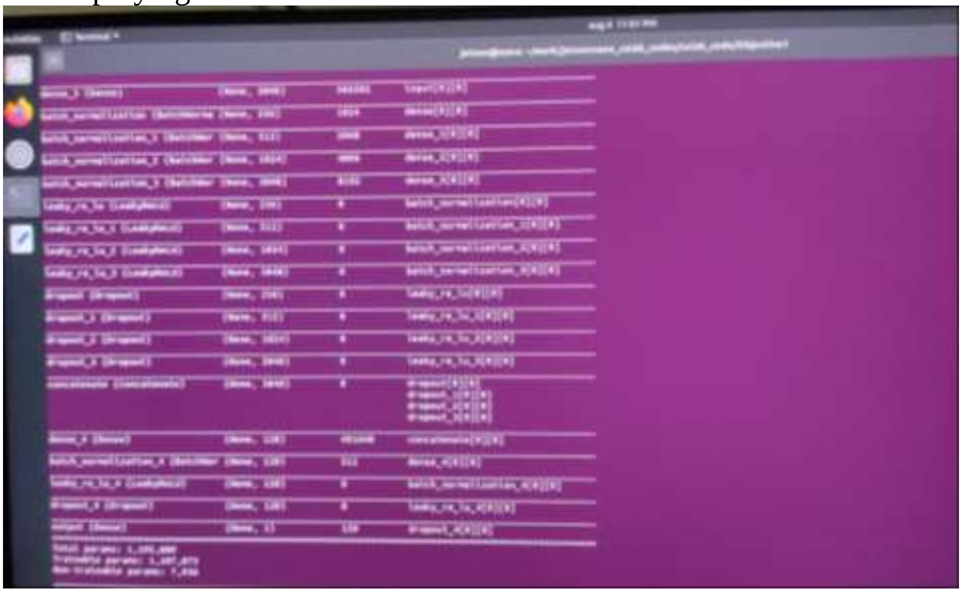

Figure 5. Proposed Model Ported on NVIDIA Jetson Nano Developer Kit

Figure 5 illustrates the proposed model for EEG signal analysis, ported onto the NVIDIA Jetson Nano Developer Kit. This setup enables efficient processing of EEG data, leveraging the Jetson Nano's edge computing capabilities to perform complex deep learning computations with reduced latency. The model architecture shown includes multiple dense layers, batch normalization, leaky ReLU activations, and dropout layers to ensure robustness and prevent overfitting. By running on the Jetson Nano, the model benefits from accelerated processing and real-time performance, making it suitable for applications in EEG signal analysis where rapid data interpretation is essential. This deployment highlights the model’s adaptability to resource-constrained hardware, supporting practical, real-time EEG analysis.

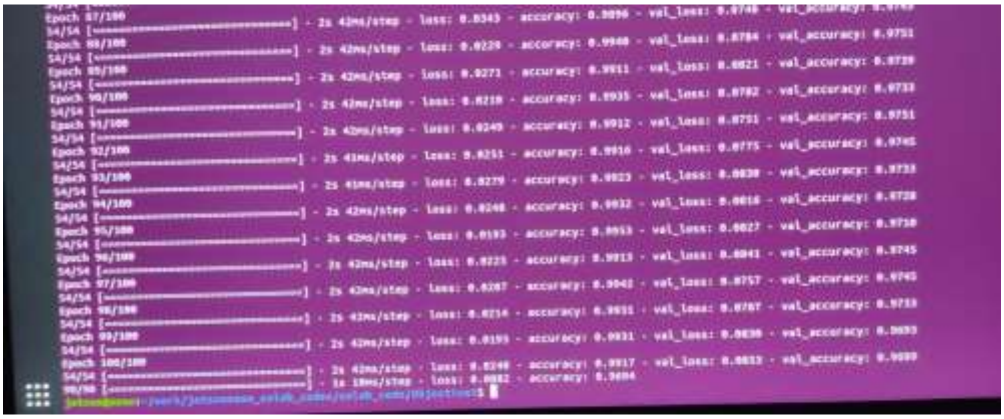

Figure 7. Energy consumption

Figure 6 shows the training epochs of the proposed model running on the NVIDIA Jetson Nano Developer Kit. The model undergoes 50 epochs, with each epoch displaying the loss, accuracy, validation loss, and validation accuracy. The training achieves consistently high accuracy, with the final validation accuracy reaching around 97.8%. The Jetson Nano's processing capabilities allow for efficient execution of each training step (42 milliseconds per step), demonstrating the device's suitability for deep learning tasks in real-time applications. This setup emphasizes the model's stability

Industrial Engineering Journal
ISSN: 0970-2555
Volume : 53, Issue 12, No. 4, December : 2024

and accuracy, making it well-suited for resource-limited environments where real-time performance is critical.

Conclusion

This study successfully integrates advanced CNN-based models for epileptic seizure and schizophrenia detection onto the NVIDIA Jetson Nano Developer Kit, demonstrating the potential for real-time, portable diagnostics. The models' robust architectures ensure efficient feature extraction and classification through techniques such as batch normalization, Leaky ReLU activations, and dropout regularization, achieving high accuracy in analyzing EEG signals. By leveraging the Jetson Nano's computational capabilities, the study reduces reliance on bulky medical equipment, offering a scalable and cost-effective solution for neurological diagnostics. These results underscore the transformative potential of combining edge AI with medical diagnostics to improve accessibility and timely intervention. Future efforts may focus on expanding the models to other neurological conditions and integrating these systems into broader healthcare networks for enhanced patient care.

References

[1] Tran, Ly V., Hieu M. Tran, Tuan M. Le, Tri TM Huynh, Hung T. Tran, and Son VT Dao. "Application of machine learning in epileptic seizure detection." Diagnostics 12, no. 11 (2022): 2879.

[2] Ciprian, Claudio, Kirill Masychev, Maryam Ravan, Akshaya Manimaran, and AnkitaAmol Deshmukh. "Diagnosing schizophrenia using effective connectivity of resting-state EEG data." Algorithms 14, no. 5 (2021): 139.

[3] Tuncer, Erdem, and Emine Doğru Bolat. "Channel based epilepsy seizure type detection from electroencephalography (EEG) signals with machine learning techniques." Biocybernetics and Biomedical Engineering 42, no. 2 (2022): 575-595.

[4] Ranjan, Rakesh, Bikash Chandra Sahana, and Ashish Kumar Bhandari. "Deep learning models for diagnosis of schizophrenia using EEG signals: emerging trends, challenges, and prospects." Archives of Computational Methods in Engineering 31, no. 4 (2024): 2345-2384.

[5] Shen, Mingkan, Peng Wen, Bo Song, and Yan Li. "An EEG based real-time epilepsy seizure detection approach using discrete wavelet transform and machine learning methods." Biomedical Signal Processing and Control 77 (2022): 103820.

[6] Kim, Jieun, Min-Young Kim, Hyukchan Kwon, Ji-Woong Kim, Woo-Young Im, Sang Min Lee, Kiwoong Kim, and Seung Jun Kim. "Feature optimization method for machine learning-based diagnosis of schizophrenia using magnetoencephalography." Journal of Neuroscience Methods 338 (2020): 108688.

[7] Kim, Minjae, Seungjae Yoo, and Chul Kim. "Miniaturization for wearable EEG systems: recording hardware and data processing." Biomedical Engineering Letters 12, no. 3 (2022): 239-250.

[8] Gonzalez, Hector A., Richard George, Shahzad Muzaffar, Javier Acevedo, Sebastian Hoeppner, Christian Mayr, Jerald Yoo, Frank HP Fitzek, and Ibrahim M. Elfadel. "Hardware acceleration of EEG-based emotion classification systems: a comprehensive survey." IEEE Transactions on Biomedical Circuits and Systems 15, no. 3 (2021): 412-442.

[9] Rasheed, Khansa, Adnan Qayyum, Junaid Qadir, Shobi Sivathamboo, Patrick Kwan, Levin Kuhlmann, Terence O'Brien, and Adeel Razi. "Machine learning for predicting epileptic seizures using EEG signals: A review." IEEE reviews in biomedical engineering 14 (2020): 139-155.

[10] Aayesha, Muhammad Bilal Qureshi, Muhammad Afzaal, Muhammad Shuaib Qureshi, and Muhammad Fayaz. "Machine learning-based EEG signals classification model for epileptic seizure detection." Multimedia Tools and Applications 80, no. 12 (2021): 17849-17877.

[11] Savadkoohi, Marzieh, Timothy Oladunni, and Lara Thompson. "A machine learning approach to epileptic seizure prediction using Electroencephalogram (EEG) Signal." Biocybernetics and Biomedical Engineering 40, no. 3 (2020): 1328-1341.

[12] De Miras, J. Ruiz, Antonio José Ibáñez-Molina, Maria Felipa Soriano, and Sergio Iglesias-Parro. "Schizophrenia classification using machine learning on resting state EEG signal." Biomedical Signal Processing and Control 79 (2023): 104233.

[13] Barros, Carla, Carlos A. Silva, and Ana P. Pinheiro. "Advanced EEG-based learning approaches to predict schizophrenia: Promises and pitfalls." Artificial intelligence in medicine 114 (2021): 102039.

[14] Hassan, Fatima, Syed Fawad Hussain, and Saeed Mian Qaisar. "Fusion of multivariate EEG signals for schizophrenia detection using CNN and machine learning techniques." Information Fusion 92 (2023): 466-478.

[15] Kim, Jeong-Youn, Hyun Seo Lee, and Seung-Hwan Lee. "EEG source network for the diagnosis of schizophrenia and the identification of subtypes based on symptom severity—A machine learning approach." Journal of Clinical Medicine 9, no. 12 (2020): 3934.

[16] Xie, Yu, and Stefan Oniga. "A Comprehensive Review of Hardware Acceleration Techniques and Convolutional Neural Networks for EEG Signals." Sensors 24, no. 17 (2024): 5813.

[17] Beeraka, Sai Manohar, Abhash Kumar, Mustafa Sameer, Sanchita Ghosh, and Bharat Gupta. "Accuracy enhancement of epileptic seizure detection: a deep learning approach with hardware realization of STFT." Circuits, Systems, and Signal Processing 41 (2022): 461-484.

[18] Xie, Yu, Tamás Majoros, and Stefan Oniga. "FPGA-based hardware accelerator on portable equipment for EEG signal patterns recognition." Electronics 11, no. 15 (2022): 2410.