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Anjar Ahsan
Faculty of Defence Science and Technology, National Defence University of Malaysia, Kuala Lumpur, Malaysia, anjarahsan@gmail.com

Hassan bin Mohammed
Cyber Security and Digital Industrial Revolution Centre, National Defence University of Malaysia, Kuala Lumpur, Malaysia

Abhilash Maroju
cDepartment of Information Technology, University of the Cumberlands USA

Nurhafizah Moziyana Mohd Yusop
Faculty of Defence Science and Technology, National Defence University of Malaysia, Kuala Lumpur, Malaysia

Wan Su Emi Yusnita Wan Yusof
Department of Management, Faculty of Defence Studies and Management, National Defence University of Malaysia, Kuala Lumpur, Malaysia

See next page for additional authors

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ORIGINAL ARTICLE

An Optimized Model for Identification of Cerebral Palsy Using Deep Learning

Md Anjar Ahsan [a,*], Hassan bin Mohammed [b], Abhilash Maroju [c], Nurhafizah Moziyana Mohd Yusop [a], Wan Su Emi Yusnita Wan Yusof [d], Najjah Salwa Abd Razak [e], Mohd Arif Dar [f,**]

[a] Faculty of Defence Science and Technology, National Defence University of Malaysia, Kuala Lumpur, Malaysia
[b] Cyber Security and Digital Industrial Revolution Centre, National Defence University of Malaysia, Kuala Lumpur, Malaysia
[c] Department of Information Technology, University of the Cumberlands USA, USA
[d] Department of Management, Faculty of Defence Studies and Management, National Defence University of Malaysia, Kuala Lumpur, Malaysia
[e] Department of Language and Culture, Language Centre, National Defence University of Malaysia, Sungai Besi Camp, 57000, Kuala Lumpur, Malaysia
[f] Center of Ionics, Department of Physic, University of Malaya, Kula Lampur 50603, Malaysia

Abstract

Cerebral palsy (CP), a neurological disorder that affects children and can occasionally result in cognitive problems as well as deficits in motor function can be caused by prenatal, perinatal, or postnatal factors. Each subtype of cerebral palsy (CP), such as spastic and non-spastic cerebral palsy, has distinct symptoms based on the location of the brain lesion and how it affects muscle tone. Individualized therapy and rehabilitation programs are necessary to treat these differences effectively. Therefore, early-stage CP categorization is crucial to ensuring timely and targeted treatment efforts. The functional magnetic resonance imaging (fMRI) of the infant's brain is a helpful technique for CP imaging and early detection. This research uses a deep convolutional neural network (CNN) based on a modified AlexNet architecture to classify CP subtypes using newborn fMRI data. The modified AlexNet architecture gives an accuracy 79.5 % which is better than the results obtained through GoogleNet, AlexNET and LeNet models. This methodology aims to assist healthcare providers in developing more targeted recuperation programs, which will ultimately improve the lives of affected teenagers.

Keywords: Cerebral palsy classification, Functional MRI, Deep convolutional neural network, AlexNet architecture, Early diagnosis and rehabilitation

1. Introduction

CP is a neurological disorder that can be caused by a non-progressive brain injury or anomaly during brain development, usually in premature neonates. It mostly affects motor functions and muscle coordination. There are two important CP that are spastic and non-spastic [1]. Spastic cerebral palsy is the most common type of cerebral palsy, characterized by increased muscle tone, which leads to stiffness and difficulty with movement. Symptoms vary depending on the severity and the areas of the body affected. Children with spastic cerebral palsy often experience muscle tightness that limits their range of motion, making movements jerky or stubborn. This stiffness can affect specific parts of the body, such as the legs (spastic diplegia), one side of the body (spastic hemiplegia), or the entire body (spastic quadriplegia). Common symptoms include difficulty walking, where children may scissor their

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* Corresponding author.
** Corresponding author.
E-mail addresses: anjarahsan@gmail.com (M.A. Ahsan), dararifphy@gmail.com (M.A. Dar).

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legs or walk on their toes due to tight leg muscles [2]. Non-spastic cerebral palsy encompasses types of CP that involve decreased or changeable muscle tone, resulting in challenges with voluntary and controlled movements. This category includes dyskinetic and ataxic cerebral palsy, each with distinct symptoms. Dyskinetic CP is characterized by involuntary movements, which may be slow and writhing (athetosis) or sudden and jerky (dystonia). These movements often affect the face, arms, and legs, making speaking, eating, or writing difficult [3]. As per the World Health Organization (WHO), the estimated frequency of cerebral palsy is 3.8 % among Indians and 10 % worldwide. Since cerebral palsy can cause a lack of initial motor or cognitive development, diagnosing the disorder in newborns can be challenging. Early diagnosis, particularly before the critical developmental phase, is essential for successful rehabilitation, such as oculomotor therapy, which boosts neuroplasticity and enhances the child's quality of life [4].

Early categorization of CP plays a critical role in determining treatment outcomes, as it enables tailored interventions that address the specific needs of the individual. Identifying the type, severity, and distribution of CP early helps clinicians design personalized therapeutic plans, including physical therapy, occupational therapy, and medical involvements, to optimize motor function, reduce complications, and improve whole quality of life. For instance, children diagnosed early with spastic CP can benefit from targeted interventions to manage muscle stiffness and prevent contractures, while those with dyskinetic CP can receive therapies focusing on movement control and posture [5]. Early categorization also facilitates the implementation of assistive technologies, medications, and, if necessary, surgical options at the most effective developmental stages. Furthermore, it allows for the timely inclusion of families in educational and support programs, ensuring they are equipped to manage their child's unique challenges [6]. Neuroimaging methods like Positron Emission Tomography (PET) and Functional Magnetic Resonance Imaging (fMRI) can be used to comprehend how the brain functions. Since fMRI is exclusively helpful for studying the remodeling of neural connections after early brain injury, it is a crucial tool for understanding neuroplasticity. Nevertheless, there are challenges when using fMRI on neonates, including head instability and anatomical variations that complicate the classification and interpretation of data [7]. fMRI data integrates with convolutional neural networks (CNNs) for classification by leveraging the spatial and temporal patterns in brain activity to identify meaningful features. fMRI captures voxel-level signals that reflect neural activity, providing high-dimensional data that represent changes in blood oxygenation levels over time. To process this complex data, CNNs, known for their ability to extract spatial hierarchies of features, are employed. The integration begins with preprocessing steps such as motion correction, spatial normalization, and smoothing, which ensure that the fMRI data is aligned and standardized. The processed data is then reshaped into 2D or 3D arrays that serve as input to the CNN [8]. These arrays preserve the spatial structure of the brain, enabling CNNs to analyze localized patterns of activity across regions. Layers of the CNN sequentially extract features, from low-level patterns (e.g., voxel intensity variations) to high-level abstractions (e.g., region-specific activation maps). Temporal information, critical in fMRI, can also be integrated through techniques like 3D-CNNs or by combining CNNs with recurrent neural networks (RNNs) to capture dynamic activity over time. The CNN learns to classify brain states, diseases, or cognitive tasks based on these patterns, enabling robust and automated analysis of complex fMRI datasets [9].

CNNs play a transformative role in designing personalized therapies by extracting and analyzing detailed patterns from complex medical data, such as medical imaging and physiological signals. CNNs are particularly adept at identifying subtle features in diagnostic images like MRI, CT scans, or X-rays that may be imperceptible to the human eye [10]. By leveraging this capability, they can detect specific biomarkers or abnormalities, enabling precise diagnosis and stratification of patients based on their unique conditions. For example, in neurological disorders, CNNs can analyze brain imaging data to identify region-specific damage or altered connectivity, aiding in the customization of targeted therapies like neurostimulation or rehabilitation exercises. In oncology, CNNs can evaluate tumor characteristics, such as size, location, and aggressiveness, guiding personalized treatment plans that combine surgery, chemotherapy, or radiation [11]. Moreover, CNNs can integrate multimodal data, such as genetic profiles and clinical history, to predict individual responses to specific treatments, ensuring more effective outcomes. This data-driven approach reduces the trial-and-error process often involved in therapy design, minimizes side effects, and optimizes resource allocation. By tailoring therapies to the unique needs of each patient, CNNs contribute to a more precise and effective healthcare system, improving quality of life and treatment success rates [12].

The severity of periventricular leukomalacia (PVL) abnormalities, such as ventricular dilatation, enlargement of the interhemispheric fissure, and bleeding, is the main emphasis of the cerebral palsy categorization systems that are now in use. These approaches mostly depend on MRI scans. Although some studies use motor abnormalities (such as diplegia, dyskinesia, and spasticity) to categorize children with cerebral palsy, these approaches are most effective when applied to children between the ages of 2 and 6. Since gross motor capabilities are challenging to evaluate at this early age, there are few methods for categorizing cerebral palsy in newborns under the age of two.

This study compares fMRI outcomes with oculomotor responses in newborns six to twelve weeks old to identify cerebral palsy. In addition, it uses a deep neural network to categorize different forms of cerebral palsy, such as dyskinetic, ataxic, mixed, and spastic. A three-layer deep neural network trained using TensorFlow is utilized to classify the kind of cerebral palsy after the fMRI images are processed via a fuzzy adaptive filter to lessen noise. After examining the photos, the classification approach produced better results in recognizing the different kinds of CP. Further, the research issues and literature in the field of cerebral palsy categorization, suggested techniques, and findings are explained.

2. Related works

Beginning in the early 1940s, studies on cerebral palsy revealed that it was a major cause of children's stunted growth. By the late 1950s, research on children with cerebral palsy-particularly those under the age of nine-had focused on how these youngsters processed information cognitively. Studies conducted in the 1960s brought attention to linguistic impairments in afflicted children, and by the 1970s, attempts were underway to investigate the etiology of cerebral palsy by examining the medical records of people with intellectual disabilities. Grants from state health departments and public health agencies frequently funded these early investigations [13]. Muscle control significantly improved in children with cerebral palsy when biofeedback training was employed to enhance motor activities, according to study conducted in the 1980s. The focus of research by the early 1990s was on how the illness affects children's motor skills and their physiological fitness. A systematic method of categorization for gross motor function in children with cerebral palsy was needed, and this was realized around the year 2000.

To close the gap between clinical research and patient treatment, a research registry was established in 2011 to promote more thorough investigations on cerebral palsy. Current studies have looked at the neurophysiological characteristics of kids with cerebral palsy and analyzed developments in pediatric cognitive rehabilitation. In an attempt to better understand the variations in gross motor function, new indices for evaluating bodily functions in subgroups of children with the disease were also developed. The usefulness of multilayer soft tissue operations in increasing patients' active mobility was assessed in surgical developments. Early in the new millennium, research examined the relationship between anomalies in the visual evoked potential (VEP) and brainstem auditory evoked potential (BAEP) in children with spastic cerebral palsy [14]. Studying the clinical trends and co-occurring conditions in impacted kids revealed that the most prevalent kind of cerebral palsy was spastic, with hypotonic, dystonic, and mixed types coming in second and third, respectively. With a male to female ratio of 1:2, the average age of diagnosis was almost two years. Studies have also looked at how cerebral palsy affects children's and families' health-related quality of life (HRQOL), with an emphasis on the connection between HRQOL and gross motor impairment [15]. Considerable advancements in patient-centered medical therapies have been acknowledged by the Indian Academy of Cerebral Palsy Rehabilitation Council. Still, comprehensive study and well-documented materials are required, particularly to assist with restoration initiatives in rural regions [16]. Classifying cerebral palsy effectively using fMRI remains a challenge, despite advancements in the field of cerebral palsy research. Greater anatomical information is needed to fully understand the intricacy of functional brain connections. In order to enable early therapy and efficient rehabilitation planning, these issues underscore the need for more reliable techniques to evaluate fMRI data from newborns, accounting for the complex changes in neurons [17].

2.1. Overview of fMRI

Functional magnetic resonance imaging (fMRI), a non-invasive technique, can measure brain activity by tracking changes in blood flow. Functional magnetic resonance imaging (fMRI) is a useful medical diagnostic technique because of its high spatial resolution and dependence on the Blood Oxygen Level Dependency (BOLD) of brain cells. The image quality is improved by applying spin echo pulses that are in line with the magnetic field's intensity and repeated stimuli. For this study, fMRI images of children with cerebral palsy were collected. Because of the complexity and non-linearity of the BOLD signal, preprocessing is necessary to remove noise, such as that created during photo attainment or by the kid subjects themselves. Thermal noise increases with the strength of the magnetic field and is reduced by using vague adaptive filters.

2.2. Fuzzy adaptive filtering

Fuzzy adaptive filtering, a more advanced version of traditional median filters, enriches image quality by eliminating unnecessary features and lowering noise without compromising important details. This technique substitutes the median value based on the levels of local noise for pixels affected by noise by comparing the intensity of each pixel to that of its neighbors. To gauge the quality of the noise-free image, the mean square error is calculated during the procedure [18]. Deep learning networks with convolution, pooling, and stacking layers employ the noise-free pictures in their training phase.

2.3. Deep learning and CNN

Throughout the 1990s, computer-aided diagnosis has played a crucial role in medical imaging, and convolutional neural networks (CNN) have made recent advances in this sector improve classifications across a range of medical specialties. The capacity of CNNs to transmit learnt features across layers, improving picture classification accuracy, makes them popular in image analysis. Examples of these CNNs include LeNet, AlexNet, and GoogLeNet.

In order to expedite training and prevent overfitting, this study uses a modified version of the AlexNet architecture that integrates non-linearity via ReLU. The design uses pooling layers to minimize the size of the picture while maintaining important features and five convolution layers for local feature detection. The max pooling layers choose features from both overlapping and non-overlapping neighbors, which leads to a more compact representation and improves translation invariance.

Regression or softmax layer produces the predicted output at the end, and back propagation (BPN) method trains CNN to minimize the cost function and increase classification accuracy.

In huge datasets, object recognition using deep learning a subset of machine learning has gained popularity lately. In order to do this, artificial neural networks are built with more layers, each of which is intended to extract unique elements that raise the accuracy of picture categorization. Subclasses are created from the preprocessed pictures in order to compute gradients, which lowers the volume of data overall and allows for parallel processing, which expedites calculation [19].

Deep learning uses Convolutional Neural Nets (CNNs) extensively for image categorization. CNNs and conventional feedforward neural networks are similar, but their layer connections are different. While feedforward networks may remove certain nodes in order to minimize complexity, CNNs have all nodes connecting neighboring layers, which can cause issues like overfitting and sluggish training times. CNNs add convolution and pooling layers to solve these problems. A tiny fraction of the preceding layer, usually 3×3 or 5×5, is taken up by the convolution layer to concentrate on important features, while the pooling layer shrinks the matrix size, reducing the number of parameters and boosting computing efficiency to prevent overfitting.

2.4. Key layers in CNNs

Convolution Layer: The feature extraction process is handled by this layer. Convolution layer neurons create feature maps, with predefined weights connecting each map to nearby neurons in the preceding layer. Despite being the same for every feature map, these weights enable the extraction of distinct features at varied intensities. The following formula yields the feature map output: Yn = f (Wn∗x)Y_n = f(W_n * x) Yn = f(Wn∗x) (1) is the formula in which non-linear features are extracted from the input by a non-linear activation function f(.)f(.)f(.), the input is xxx, and the convolution window for the nth feature map is WnW_nWn

Pooling Layer: This layer improves spatial invariance to input distortions while decreasing the feature maps' spatial resolution. It either employs max pooling, which chooses the neighborhood's maximum value, or average pooling, which passes the average value of a small neighborhood to the following layer [20].

Stacked Layers: Several convolution and pooling layers are placed on top of one another to capture increasingly intricate characteristics. A softmax operator, which is frequently employed in conjunction with the Back Propagation Training (BPT) method for classification issues, is utilized to produce the final classification. The multidimensional vector that the softmax output creates normalizes class scores into probabilities between 0 and 1. Softmax's ability to divide the network's confidence among many classes makes it very useful for picture classification problems [21].

3. Methodology

This study aims to enhance rehabilitation planning by improving the early diagnosis of cerebral palsy, especially in babies between the ages of six and sixteen months. The technique tackles the current difficulties in fMRI analysis and gross motor response correlation [22]. The suggested method makes use of a modified version of the AlexNet architecture, which consists of two completely linked layers after five convolution layers. To map feature units and normalize local responses per four pixels, the first convolution layer has a 12 × 12 kernel size. This produces ninety-six feature maps. After that, there is a second convolution layer and a pooling layer with a kernel size of 6 and a stride rate of 2. The pooling and convolution processes result in two fully connected layers that perform corrected linear computations and 4096 feature maps are produced using this structure for each input image. Fig. 1 shows the schematic diagram of the proposed work.

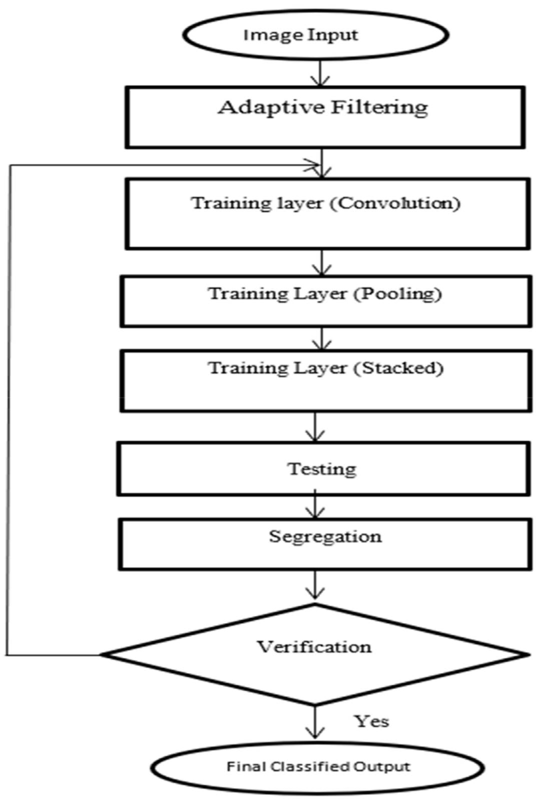

Fig. 1. schematic diagram of the proposed work.

4. Results

Infants' fMRI data were gathered from a number of publicly available neuroimaging databases, such as OpenNeuro, StarPlus fMRI, CRCNS, and OASIS. Fuzzy adaptive mean filtering was used to preprocess these photos in order to eliminate drift components, seasonal changes, and noise.

4.1. Testing and training

The training step employed the datasets that were procured from various web-based sources. The datasets were classified by the kind of cerebral palsy and the age of the newborns, even though particular categorization isn't usually required in machine learning because the goal of this research is to classify medical photographs. Fig. 2 displays sample fMRI scans of newborns with different forms of cerebral palsy [23] and Fig. 3 show the recent advances in cerebral palsy [24].

4.2. Pre-training

TensorFlow is an open-source framework that provides multilayer neural network construction

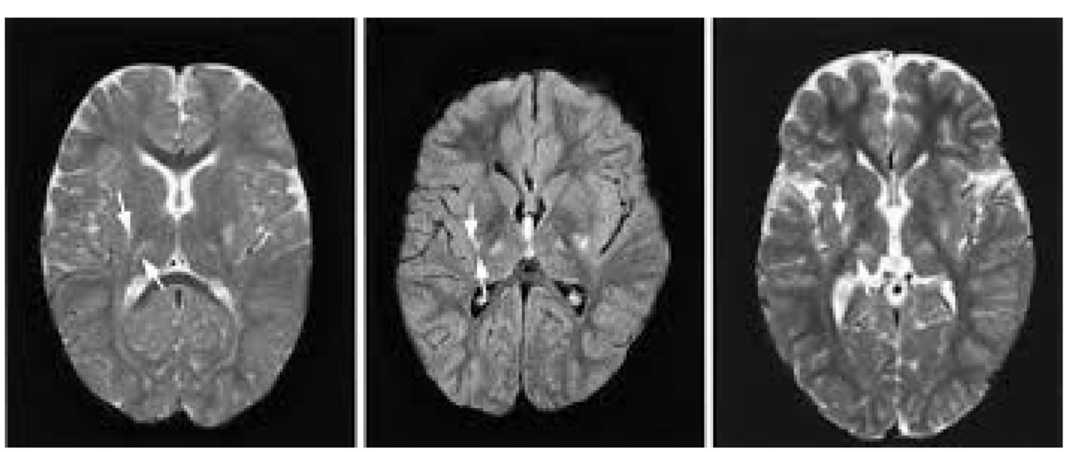

Fig. 2. fMRI scans of newborns with different forms of cerebral palsy [23].

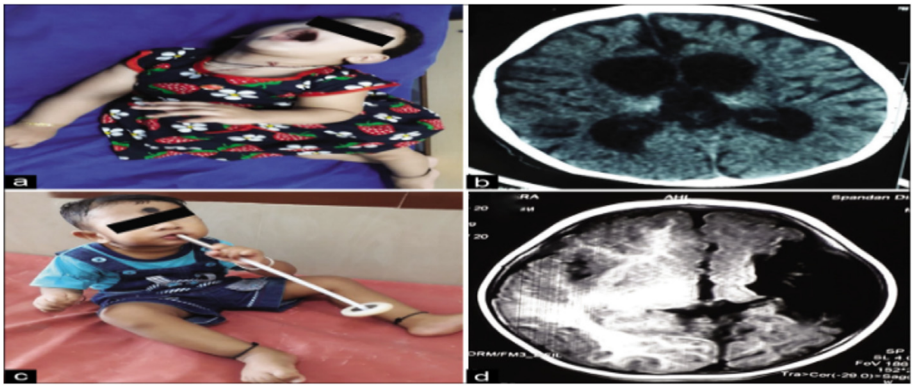

Fig. 3. Recent advances in cerebral palsy [24].

and training capabilities, and it was used in the experimentation. For training and testing purposes, a total of 217 fMRI scans and 120 pictures were utilized. The softmax function was utilized to transform the CNN output nodes into class probabilities, and the loss function represented the error between the anticipated and actual output classes. The scarcity of labeled datasets is a significant obstacle to CNN model training for medical image analysis. Few fMRI datasets are accessible for study, including CRCNS, StarPlus fMRI, and neuroimaging data. As indicated in Table 1 and the bar diagram shown in Fig. 4, the final output layers were trained using real-time fMRI scans from the Cerebral Palsy Society. The neural network was trained again and again until the loss function was reduced by changing the weights. The training loss was mapped against iterations to gauge progress. As shown each iteration employed 20 photos, and the accuracy of each dataset was monitored in conjunction with the loss function transfer learning was used to overcome the shortcomings of limited datasets. Assuming that important visual characteristics are shared throughout the datasets, weights from bigger datasets were utilized to train the smaller dataset [25—28].

Whereas transfer learning offers significant advantages, such as leveraging pre-trained models to address tasks with limited data, it has notable limitations in such scenarios. One key challenge is that the pre-trained model may not generalize well to the new domain if the source and target datasets differ significantly in features or distribution. For instance, a model trained on natural images (e.g., ImageNet) may struggle to adapt to medical imaging data due to differences in textures, shapes, and content, potentially leading to suboptimal performance. Another limitation is the risk of overfitting, particularly when the target dataset is very small. Fine-tuning the pre-trained model with insufficient data can cause it to memorize specific examples instead of learning generalized patterns. This issue is exacerbated if the original model is overly complex, as its vast number of parameters requires a substantial amount of data to adjust effectively. Additionally, transfer learning can introduce biases from the source model, which may not align with the target task's requirements. For example, pre-trained models might inadvertently carry biases from their training data, leading to skewed results in the new application. Lastly, computational demands for fine-tuning can be high, especially for large models, making it resource-intensive even when data is scarce. These limitations highlight the need for careful adaptation techniques and domain-specific adjustments.

Table 1. Final output layers.

Image Category	Training	Test	Total
Spastic	89	44	133
Dyskinetic	54	25	79
Ataxic	26	17	43
Mixed	48	34	82
Total	**217**	**120**	337

4.3. Comparative result analysis

There were training and testing phases in the research experiment, and each set ran for 150 epochs. Accuracy increased and loss reduced as training went on. Because fMRI data is time-series and 3D, classifying it has proven to be more difficult than typical MRI image training. The three-layer CNN model yielded the maximum accuracy of 66.8 % with concentrated hyper parameter optimization; improved convergence was observed with double the length of data. By grouping the photos into five groups of twenty images each, a confusion matrix was used to assess the algorithm's performance. As seen in Table 2 and the bar diagram shown in Fig. 5, the confusion matrix helped

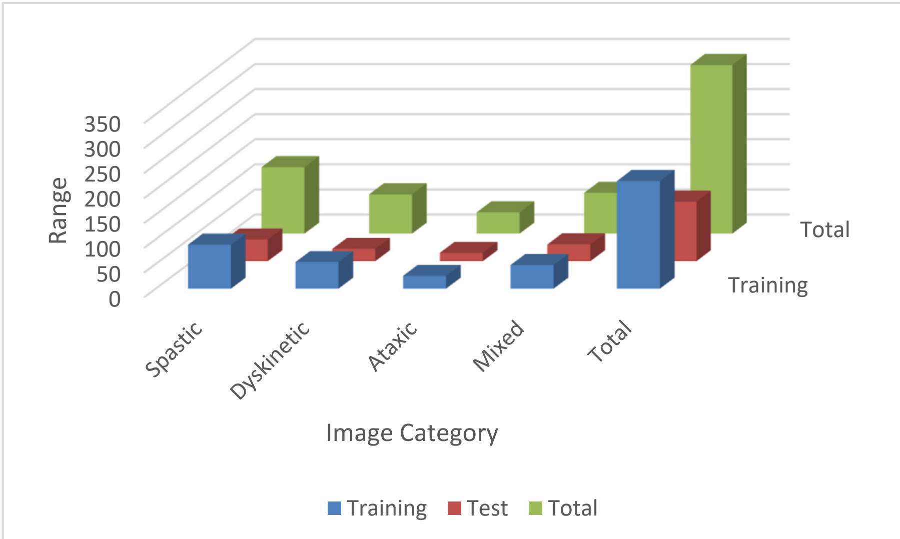

Fig. 4. Final output layers.

Table 2. Confusion matrix for three test cases.

Details	Case 1	Case 2	Case 3
TP	14	18	13
FP	3	1	3
TN	4	3	4
FN	2	2	3
Accuracy	**0.78**	**0.89**	**0.76**

determine the proportion of pictures that were accurately categorized by kind of cerebral palsy. With a modified deep learning model, our goal in this work was to improve the classification accuracy of fMRI pictures of newborns with cerebral palsy (CP). True Positives (TP), False Positives (FP), True Negatives (TN), and False Negatives (FN) were the measures used to assess the performance. The capacity of the system to properly or erroneously categorize fMRI pictures depending on the inputs produced distinct findings for each test run. The results from three test instances are summarized here:

Let's explore the meaning of these values now. Assume you are examining a collection of fMRI scans. When a picture is accurately categorized as being impacted by CP, it is said to have a **True Positive (TP)**. This is when the algorithm performs best. **Case 1** yielded 14 correctly identified photos, while **Case 2** produced an astounding 18 correctly categorized images. Conversely, **False Positives (FP)** happen when the system incorrectly marks a picture as impacted by CP when it isn't. The algorithm produced three of these mistakes in **Case 1**, but only one in **Case 2**, suggesting better model performance. Likewise, **True Negatives (TN)** record the frequency with which the system appropriately classifies photos as unaffected. In **Case 1**, it successfully identified four objects, matching **Case 3** in terms of accurately named unaffected photos. However, no algorithm is flawless. The photos influenced by CP that escaped the algorithm's grasp and were incorrectly labeled are known as **False Negatives (FN)**. **Cases 1 and 2** performed better in identifying impacted photographs than **Case 3**, which had the most of these three.

4.3.1. Understanding key metrics

Three key criteria were utilized to assess the model's performance: accuracy, recall, and precision.

- To calculate **Precision**, divide the total number of instances categorized as positive (TP + FP) by the number of properly detected positive cases (TP). This statistic aids in our comprehension of how trustworthy the algorithm is when it indicates that CP has an impact on a picture.
- By dividing the total real positives (TP + FN) by the true positives (TP), **Recall** provides an estimate of the model's accuracy in identifying all genuine instances of cystic fibrosis.
- The most widely known indicator, **Accuracy**, determines the percentage of positive and negative pictures in the dataset that were properly identified.

4.3.2. Experimental Results

This shows how automated algorithms may help improve the precision of diagnosis. We next

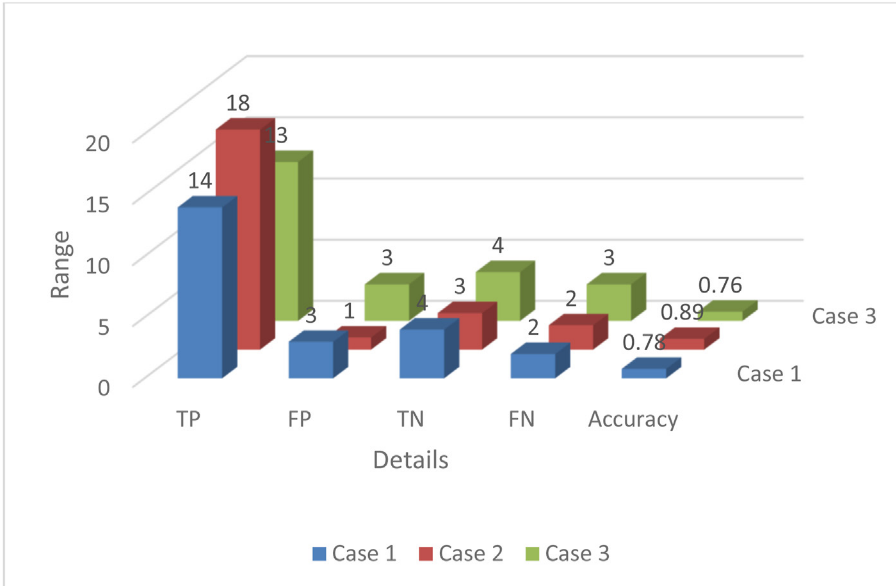

Fig. 5. Confusion Matrix for Three Test Cases.

contrasted our findings with those of other well-known models, including LeNet, AlexNet, and GoogleNet. How our **Modified AlexNet** fared in evaluation to various models is displayed in the following Table 3 and bar diagram Fig. 6. The results validate that, in terms of test validity and accuracy, our modified AlexNet performed better than the others. The model shown significant ability to classify cerebral palsy with remarkable accuracy by adjusting the number of convolutional layers, kernel

Table 3. Comparative performance of various models.

Method	Runtime (sec)	Training Loss	Validation Accuracy (%)	Test Accuracy (%)
GoogleNet	1750	1.7	68	66
AlexNet	35,470	1.5	76	72
LeNet	54,600	1.6	55	57
Modified AlexNet	**16,950**	**0.85**	**82.1**	**79.5**

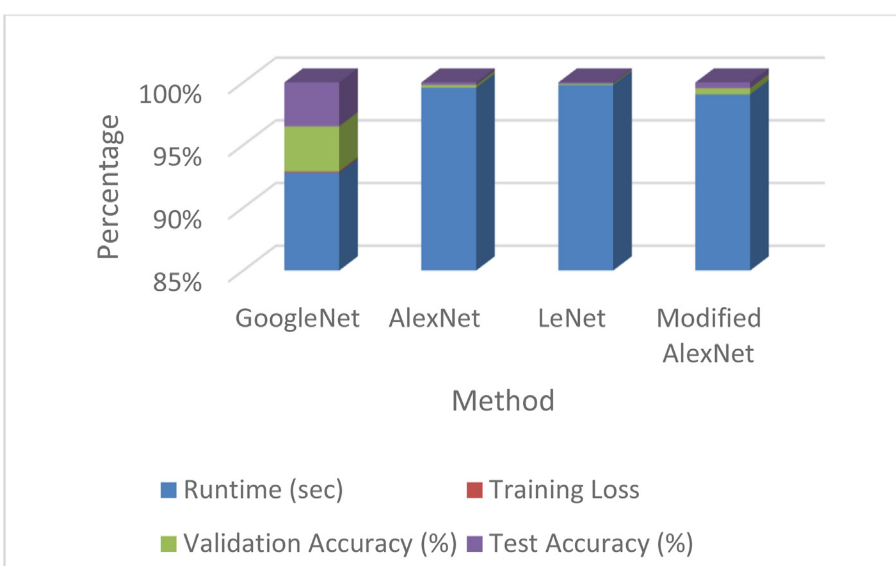

Fig. 6. Comparative Performance of Various Models.

size, and stride rate. There is still opportunity for progress, thus the search is far from over. Nevertheless, this research provides reassuring proof that customized deep learning models, such as the Altered AlexNet, can revolutionize medical imaging by enabling more precise diagnosis and even helping radiologists make verdicts more quickly.

5. Conclusion and Future Scope

In this work, we introduce a novel design for a convolutional neural network (CNN) based on AlexNet to grow the classification accuracy of fMRI brain images in neonates with cerebral palsy. Our model enhances picture classification accuracy and precision by using 5 convolutional layers and stacked pooling layers. These experimental results validate that our suggested deep learning network outperforms existing methods and efficiently addresses the difficulties in obtaining fMRI data from neonates. The rich features gleaned from the limited number of samples pointedly aided in the accurate classification of cerebral palsy, despite the limited availability of medical imaging datasets due to privacy and security concerns. We intend to expand on this study in the future by developing a broader network that classifies the many types of cerebral palsy. This will involve integrating fMRI data with oculomotor response measurements to enhance classification precision and provide a more thorough knowledge of the disorder.

Ethics information

None.

Authors' contributions

Md Anjar Ahsan: Conceptualization, methodology, visualization, writing-original draft.

Mohd Arif Dar: Conceptualization, Review and Editing.

Dr. Hassan bin Mohammed: Methodology, Review and Editing.

Dr. Abhilash Maroju: Visualization, software.

Nurhafizah Moziyana Mohd Yusop: Resources.

Wan Su Emi Yusnita Wan Yusof: Resources.

Najjah Salwa Abd Razak: Resources.

AI usage declaration

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Conflict of interest

The authors state that they do not have any conflicts of interest to disclose in relation to this work.

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