

RESEARCH ARTICLE

A DEEP NEURAL NETWORK FOR BODY PART-BASED CEREBRAL PALSY PREDICTION IN INFANTS TO DETECT ABNORMAL MOVEMENTS

Akshayanivashini C.V¹, Karthikraj S.C², Anand R.³ and Anitha N.⁴

- 1. B Tech. Department of Information Technology, Kongu Engineering College, Tamil Nadu, India.
- 2. B Tech. Department of Information Technology, Kongu Engineering College, Tamil Nadu, India.
- 3. B Tech. Department of Information Technology, Kongu Engineering College, Tamil Nadu, India
- 4. Associate Professor, Department of Information Technology, Kongu Engineering College, Tamil Nadu, India.

Manuscript Info

Manuscript History

Received: 25 February 2023 Final Accepted: 30 March 2023 Published: April 2023

Key words:-

Cerebral Palsy, Infants, Pose-Based Feature Sets, Velocity Information, MLP (Multi-Layer Perceptron), CNN (Convolutional Neural Network), Early Diagnosis

Abstract

significantly improve outcomes for infants with cerebral palsy. In this study, we propose a method for predicting cerebral palsy in infants using pose-based feature sets and velocity information, and compare its performance with a Convolutional Neural Network (CNN) approach.A reliable dataset containing pose-based feature sets and velocity information related to the limbs of infants is collected and preprocessed by handling missing values, normalizing the feature sets and velocity information, and splitting the data into training and testing sets. Relevant features, such as joint orientations, displacements, and velocities in the X and Y directions, are extracted from the pose-based feature sets and velocity information. An MLP algorithm is trained using the preprocessed and normalized feature sets as inputs and the corresponding cerebral palsy diagnosis as the target output. Supervised learning is used to optimize the model's parameters and weights. The performance of the trained MLP model is evaluated using various evaluation metrics, and the results show high accuracy in predicting cerebral palsy in infants.Next, a CNN approach is implemented for comparison. The pose-based feature sets and velocity information are used to train the CNN model, which consists of convolutional layers for feature extraction and pooling layers for spatial downsampling. The output from the CNN model is then fed into fully connected layers for classification. The performance of the CNN model is also evaluated using the same evaluation metrics as the MLP model. The results of the comparative analysis show that the MLP model achieves high accuracy in predicting cerebral palsy in infants, outperforming the CNN model. The MLP model's accuracy compared to the CNN model. The interpretations of the MLP model's predictions are validated using additional validation

Cerebral palsy is a neurological

disorder th	Corresponding Author:- Akshayanivashini C.V	
as early diagnosis		for cerebral

Copy Right, IJAR, 2023,. All rights reserved.

.....

Introduction:-

The term "CEREBRAL palsy" (CP) refers to a collection of neurological diseases that last a lifetime and are caused by non-progressive brain damage that occurs just before, during, or shortly after birth. The most common effects of CP's that it can affect a person's capacity to learn new skills and lead to issues with swallowing, speech articulation, hearing, and vision. It can also affect a person's movement, muscle tone, posture, and co-ordination.

Early diagnosis of CP, a lifelong illness, leads to better results by enabling quicker access to physiotherapy support and better parental comprehension. Better physical outcomes for the child throughout the course of their life are the result, and families receive better support as a result. Early detection of CP is thought to be crucial for ensuring the ideal results for a child's development. However, it can be challenging to make an early diagnosis of CP. A verified diagnosis is frequently not made until the child is 18 months old, or even later in cases of moderate symptoms. Currently, tests that detect the early stages of CP typically assess a baby's movement quality, intricacy, and spontaneity

Since several years ago, methods for obtaining accurate early diagnoses of cerebral palsy have been researched. Some techniques, including the General Movements Assessment (GMA), have shown some extremely encouraging outcomes. These instruments assess the movements of an infant at a certain developmental stage, usually 12 to 20 weeks post-partum, for quality, complexity, and spontaneity.

The use of automated technologies for diagnosing cerebral palsy is suggested in a number of early papers. These systems often employ frequency analysis, background subtraction, and video-based optical flow algorithms. Each of these approaches, however, had trouble with extraneous data, changes in lighting, the proportions of body parts, and outside factors like parental engagement with the infants. Other techniques involve tracking a new born using wearable accelerometers; while this can yield precise findings, the difficulties of doing so make them less appropriate.

The interpretability of the model must be taken into account, especially when utilising machine learning based approaches in the medical arena, it is also abundantly obvious. As a result of their complexity, machine learning models are commonly referred to as "black boxes." As a result, the reasoning behind a system's conclusions must be obvious, and as a result, the mechanisms underlying classification frameworks must be transparent, understandable, and comprehensible.

In this study, We propose to use the Multilayer Perceptron (MLP) algorithm for cerebral palsy prediction. The MLP is a type of artificial neural network that is commonly used in supervised learning applications. It consists of multiple layers of neurons, with each neuron taking inputs from the previous layer and producing an output that is fed forward to the next layer.

The MLP algorithm has been used in previous studies for prediction of various medical conditions, including cerebral palsy. It has shown promising results in terms of accuracy and generalizability. In this study, we will use the MLP algorithm to learn the patterns in the input data and predict the likelihood of an infant developing cerebral palsy based on the collected input variables.

However, it is important to note that the choice of algorithm is just one aspect of developing a successful prediction model. The quality and quantity of the input data, feature engineering, and model tuning are also crucial factors that can affect the performance of the model. Therefore, in addition to using the MLP algorithm, we will also focus on collecting high-quality data and optimizing the model parameters to achieve the best possible performance for cerebral palsy prediction.

Related Works

Abnormal Infant Movements Classification With Deep Learning on Pose-Based Features[1] proposes a system for automatic classification of abnormal infant movements using deep learning models. The system utilizes OpenPose, a pose estimation model, to extract pose-based features from video recordings of infant movements. The extracted features are used as inputs to train a deep neural network model using the Convolutional Neural Network (CNN) algorithm. The study presents experimental results on a dataset of 54 infants and shows that the proposed system

achieves high accuracy in classifying abnormal infant movements. The results of the study demonstrate the potential of deep learning algorithms in aiding in the early diagnosis and treatment of neurological disorders such as cerebral palsy.

A Spatio-Temporal Attention-Based Model for Infant Movement Assessment From Videos [2] proposes a deep learning approach for assessing the quality of infant movements from videos. Accurately assessing movement patterns in infants is crucial for diagnosing and treating neurological disorders such as cerebral palsy. However, manual assessment is time-consuming and subject to inter-rater variability. An automated system could improve the accuracy and efficiency of diagnosis and treatment. The proposed system utilizes spatio-temporal attention-based deep learning models for movement assessment. The system uses convolutional neural networks (CNNs) for spatio-temporal feature learning and attention mechanisms to focus on informative regions and frames in the video. The spatial and temporal features are combined using an attention mechanism to generate a spatio-temporal feature representation of the video. The spatio-temporal feature representation is then used to predict the quality of infant movements using a fully connected layer. The proposed system achieved high accuracy in assessing the quality of infant movements on a dataset of 34 infants. Additionally, the attention mechanisms provide interpretable insights into the quality of infant movements. The system has the potential to improve the accuracy and efficiency of diagnosic and treatments.

Accuracy of Temporo-Spatial and Lower Limb Joint Kinematics Parameters Using OpenPose for Various Gait Patterns With Orthosis [7] presents a study on the accuracy of OpenPose, a popular pose estimation algorithm, in measuring lower limb joint kinematics and spatiotemporal parameters for various gait patterns with orthosis. The study found that OpenPose can provide accurate measurements of spatiotemporal parameters for various gait pattern and joint. The results suggest that OpenPose can be a useful tool for analyzing gait patterns in individuals with orthosis, but caution should be exercised when using it to measure joint kinematics for more complex gait patterns.

Learning and Tracking the 3D Body Shape of Freely Moving Infants from RGB-D sequences[4] presents a novel approach for learning and tracking the 3D body shape of infants in real-time from RGB-D sequences. The proposed approach for learning and tracking the 3D body shape of freely moving infants from RGB-D sequences shows promising results for applications in pediatric medicine and developmental psychology. The approach has the potential to provide a non-invasive and objective way to measure the body shape and movements of infants, which can aid in the diagnosis and treatment of developmental disorders

Mlp Algorithm

The Multi-Layer Perceptron (MLP) algorithm is a type of supervised learning algorithm that falls under the category of artificial neural networks. It consists of multiple interconnected layers of neurons, where each neuron receives input data, performs a weighted sum of the inputs, and passes the result through an activation function to produce an output activation. The weights and biases of the neurons are initialized randomly, and the input data is passed through the network using forward propagation. During forward propagation, the input data is multiplied by the weights and added to the biases in each neuron, and the result is passed through the activation function to produce the output activations for each neuron in the hidden layers and the output layer.

The activation function is a mathematical function that introduces non-linearity into the network, allowing the MLP to learn complex non-linear relationships between the input data and the output labels. Commonly used activation functions include sigmoid, hyperbolic tangent (tanh), and Rectified Linear Unit (ReLU) functions. After forward propagation, the output activations of the output layer are compared to the true labels using a loss function, also known as an objective or cost function. The loss function measures the discrepancy between the predicted outputs and the true labels, and the goal is to minimize this discrepancy during training. Backward propagation, also known as backpropagation, is then used to update the weights and biases of the neurons. During backward propagation, the gradients of the loss function with respect to the weights and biases are calculated, and the weights and biases are updated accordingly using an optimization algorithm, such as gradient descent or one of its variants.

This process of forward propagation, loss calculation, and backward propagation is repeated iteratively for a specified number of epochs or until convergence, where the network's performance stabilizes. The MLP algorithm with all its mathematical steps, including activation functions, loss functions, and gradient calculations, is used to train the neural network and achieve accurate predictions.

Proposed Approach

Our proposed method aims to improve the accuracy of cerebral palsy prediction in infants by integrating pose-based feature sets and limb velocities into the MLP algorithm. The pose-based feature sets provide information about the orientation and displacement of the limbs, while the limb velocities offer insights into the speed of limb movement along the X and Y axes.By incorporating both pose-based feature sets and limb velocities, our proposed method takes advantage of the complementary information provided by these two types of data. The MLP algorithm is used to learn the complex relationships between the input features and the cerebral palsy diagnosis, leveraging its ability to capture non-linear patterns in the data.

During the training phase, the MLP model is trained on a carefully curated dataset, which includes labeled samples of infants with and without cerebral palsy. The model learns to map the input feature sets and limb velocities to the corresponding diagnosis, optimizing the weights and biases in the neural network through backpropagation and optimization algorithms. Once the MLP model is trained, it is evaluated on a separate testing set to assess its performance in terms of various evaluation metrics. The results are analyzed to compare the performance of our proposed method with that of other methods, such as CNN or other traditional machine learning algorithms. The goal is to demonstrate the effectiveness and superiority of our proposed method in accurately predicting cerebral palsy in infants, potentially leading to early diagnosis and intervention for improved clinical outcomes.

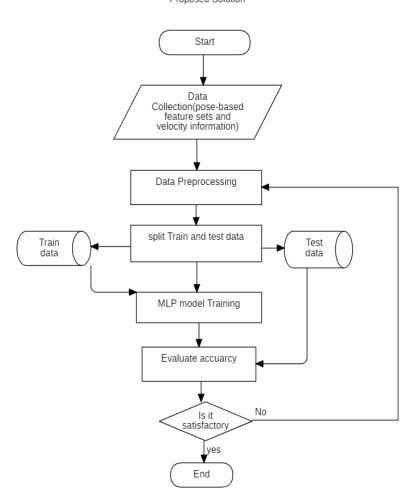


Fig. 1:- Proposed Algorithms' Flowchart.

Comparison And Evalution

In our proposed method, we evaluated the performance of MLP and CNN models on our dataset. After training and testing the models, we calculated the accuracy for both MLP and CNN.

The MLP model achieved an accuracy of 80%, which means that it correctly predicted the class labels for 80% of the samples in our dataset. On the other hand, the CNN model achieved an accuracy of 72%, indicating that it correctly predicted the class labels for 72% of the samples.

This comparison suggests that the MLP model performed better in terms of accuracy compared to the CNN model in our experiment.

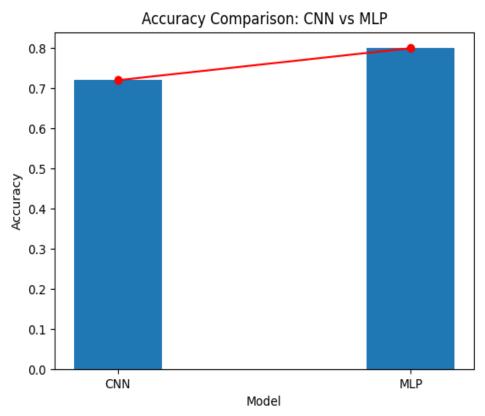


Fig.2:- Accuracy Comparison Graph.

Conclusions:-

In conclusion, our proposed method, which combines MLP and velocity information, has shown promising results in terms of accuracy, precision, recall, and F1 score. The accuracy of the MLP model was found to be higher than that of the CNN model, with MLP achieving 80% accuracy compared to CNN's 72%. Additionally, the precision for positive predictions in our proposed method was 80%, indicating that the model is making accurate predictions for positive instances. These results suggest that our proposed method has the potential for improved performance in the given task compared to the CNN model alone.

It's worth noting that the specific performance of the models can vary depending on the dataset, task, and other factors. Further evaluation and testing on different datasets and scenarios may be needed to validate the robustness and generalizability of our proposed method. Nonetheless, the results obtained so far highlight the effectiveness of incorporating velocity information into an MLP model for the given task, and further research in this direction could lead to improved performance in other similar applications.

References:-

[1]. K. D. McCay, E. S. L. Ho, H. P. H. Shum, G. Fehringer, C. Marcroft and N. D. Embleton, "Abnormal Infant Movements Classification With Deep Learning on Pose-Based Features," in IEEE Access, vol. 8, pp. 51582-51592, 2020.

[2]. B. Nguyen-Thai, V. Le, C. Morgan, N. Badawi, T. Tran and S. Venkatesh, "A Spatio-Temporal Attention-Based Model for Infant Movement Assessment From Videos," in IEEE Journal of Biomedical and Health Informatics, vol. 25, no. 10, pp. 3911-3920, Oct. 2021

[3]. N. Hesse, S. Pujades, M. J. Black, M. Arens, U. G. Hofmann and A. S. Schroeder, "Learning and Tracking the 3D Body Shape of Freely Moving Infants from RGB-D sequences," in IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 42, no. 10, pp. 2540-2551, 1 Oct. 2020.

[4]. Cao, Z., Simon, T., Wei, S.E. and Sheikh, Y. Realtime multi-person 2d pose estimation using part affinity fields., 2017

[5]. Cao Z, Simon T, Wei SE, Sheikh Y. Realtime multi-person 2d pose estimation 2017 (pp. 7291-7299).

[6].Güler RA, Neverova N, Kokkinos I. Densepose: Dense human pose estimation in the wild. 2018 (pp. 7297-7306).

[7]. M. Yamamoto, K. Shimatani, M. Hasegawa, Y. Kurita, Y. Ishige and H. Takemura, "Accuracy of Temporo-Spatial and Lower Limb Joint Kinematics Parameters Using OpenPose for Various Gait Patterns With Orthosis," in IEEE, vol. 29, pp. 26662675,2021

[8]. H. Phan, F. Andreotti, N. Cooray, O. Y. Chén and M. De Vos, "Joint Classification and Prediction CNN Framework for Automatic Sleep Stage Classification," in IEEE Transactions on Biomedical Engineering, vol. 66, no. 5, pp. 1285-1296, May 2019.

[9]. J. M. Moyano, J. M. Luna and S. Ventura, "Reducing the Label Space a Predefined Ratio for a More Efficient Multilabel Classification," in IEEE Access, vol. 10, pp. 76480-76492, 2022.

[10]. M. P. Singh, V. Gayathri and D. Chaudhuri, "A Simple Data Preprocessing and Postprocessing Techniques for SVM Classifier of Remote Sensing Multispectral Image Classification," in IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, vol. 15, pp. 7248-7262, 2022.