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Deep Learning Techniques for Abnormal & Normal Gait Classification

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ABSTRACT :

Human Gait analysis is crucial in detecting and classifying abnormal gestures in the movement patterns because of physical disabilities. The research paper is about gesture classification of normal and abnormal gestures using the Microsoft Kinect Gesture Dataset. It consists of 594 sequences and 719,359 frames and their respective videos capturing their movements. The pose estimation technique gives landmarks and skeletal structures represented as a graph. Gait classification uses deep learning algorithms such as ResNet. In addition, the performance of traditional machine learning algorithms like Random Forest Classifier, K-Nearest Neighbors (KNN), Decision Tree Classifier, and Gaussian Naive Bayes (GaussianNB) is tested and compared with deep learning models. Through experimental analysis, it has been found that deep learning models like ResNet are significantly more accurate in differentiating between normal and abnormal gait patterns than conventional machine learning algorithms. The proposed method offers valuable insights into the effectiveness of deep learning algorithms in gait classification, thereby enhancing diagnostic procedures and intervention strategies for individuals with gait abnormalities.

Keywords: Human gait Classification, Deep Learning, ResNet, KNN, Gaussian Naive Bayes (GaussianNB), Random Forest Classifier.

1. INTRODUCTION :

Human gait analysis is crucial for diagnosing physical impairments in the gait pattern to create targeted interventions for the enhancement of mobility and quality of life. Gait abnormalities caused by muscle tone disorders, weakness, or decreased range of motion of the joint contribute significantly to the impairment of daily activities and fall risks. This study proposes to classify normal and abnormal gestures using the Microsoft Research Cambridge-12 Kinect Gesture dataset and evaluate the performance of ResNet, a deep learning algorithm, in comparison with more traditional methods such as Random Forest, K-Nearest Neighbors, and Gaussian Naive Bayes. The dataset consists of 594 sequences, 719,359 frames, and high accuracy tracks of 20 joints.

Deep learning models, such as ResNet, have proven to be superior in gait analysis by automatically learning complex features from raw data, unlike traditional algorithms that rely on manual feature extraction. ResNet's hierarchical architecture allows for accurate classification of normal and abnormal gaits, outperforming conventional methods on complex datasets. This study reflects the possibilities that deep learning will provide to improve gait analysis systems and provide knowledge regarding advantages and limitations offered by various approaches to augment the diagnosis and treatment of ailments.

1.1. About the Dataset

The Microsoft Research Cambridge-12 Kinect Gesture dataset is a rich set designed to enable the analysis and classification of human movements. It comprises 594 sequences that amount to 719,359 frames or approximately six hours and 40 minutes of data. Captured from 30 individuals performing 12 different gestures, the dataset contains 6,244 instances of gestures. Each sequence contains motion files that follow 20 joints estimated from the Kinect Pose Estimation pipeline, thus providing a very accurate representation of skeletal movements.

2. LITERATURE REVIEW :

Gait analysis plays a crucial role in understanding human locomotion and identifying abnormalities associated with neurological and musculoskeletal conditions. Machine learning and deep learning techniques have been extensively applied to enhance accuracy, automate detection, and improve clinical diagnosis. Numerous studies have explored the application of these methods, demonstrating their effectiveness in various aspects of gait analysis. Supervised machine learning techniques have been successfully employed in this domain. A study by Khera and Kumar (2020) achieved accuracies exceeding 90%, identifying Support Vector Machines (SVM) as the most effective classifier for detecting disorders, predicting rehabilitation outcomes, and aiding in clinical diagnoses. Similarly, Mehrizi et al. (2019) utilized Deep Neural Networks (DNNs) for automatic health problem detection from gait videos, achieving classification accuracies between 56% and 96%, highlighting the potential of DNNs in pathological gait diagnosis.

Long Short-Term Memory (LSTM) networks have also shown promise. Potluri et al. (2019) developed a system using wearable sensors and a visual interface to detect abnormal gait behavior. Their stacked LSTM network successfully identified features like asymmetrical footing phases, reduced step length, and deviations in cadence. Additionally, Jun et al. (2021) proposed a hybrid model combining Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN), utilizing 3D skeleton and plantar foot pressure data to achieve an impressive classification accuracy of 97.6% after fine-tuning. Artificial Neural Networks (ANN) have also been applied, particularly with electromyography (EMG) data. Morbidoni et al. (2019) introduced a deep learning approach to classify gait phases during level-ground walking, achieving high accuracy in predicting phase transitions using surface EMG signals. Their method eliminated the need for manual feature engineering, significantly enhancing network performance. Similarly, CNNs have been shown to outperform traditional techniques such as SVMs and KNNs in distinguishing gait disorders, as demonstrated by Fricke et al. (2021).

Deep Neural Networks (DNNs) have also proven effective in gait identification. Mallikarjuna et al. (2019) leveraged feedback-based DNN classification to accurately detect neuropathic gait disorders, highlighting the role of DNNs in abnormality detection. Matsushita et al. (2021) further evaluated deep learning applications in clinical gait analysis, demonstrating high accuracy with CNNs, RNNs, LSTMs, and Autoencoders. Their study emphasized the need to address challenges related to computational resource limitations and data privacy in IoT-based gait analysis systems. These studies collectively underscore the potential of machine learning and deep learning techniques in advancing gait analysis, improving diagnostic precision, and supporting effective intervention strategies.

3. METHODOLOGY :

3.1. Machine Learning in Gait Classification

The current study uses baseline traditional machine learning techniques in order to classify normal and abnormal gait patterns. Algorithms include SVM, Random Forest Classifier, K-Nearest Neighbors, and Decision Tree Classifier. All the models depend on manually engineered features extracted from the Microsoft Research Cambridge-12 Kinect Gesture dataset. Key features such as angles at joints, stride lengths, and cadence are calculated in characterizing gait patterns. Preprocessing of data also involves filling up missing data points, normalization of coordinates, and gait sequence segmentation, thus maintaining consistent feature representations. All these traditional methods are checked with respect to the accuracy they provide, in terms of precision, recall, and F1 score. Fig. 1 shows how machine learning algorithms are used to classify abnormal and normal gait.

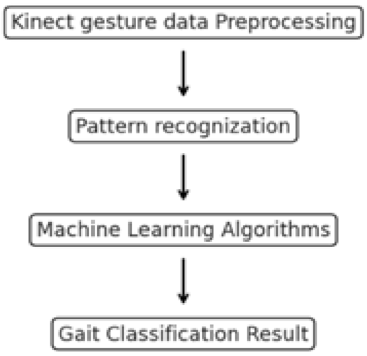

Fig. 1 ML Algorithms on Gait Classification

3.2. Deep Learning in Gait Classification

Deep learning is an element of artificial intelligence that uses neural networks for automatic learning and pattern extraction in very high-dimensional data. That gives it the edge it enjoys in classifying the gait patterns that appear to be normal or otherwise; it is beyond ordinary techniques in machine learning. This is because these deep models, such as GCNs, ResNet, CNNs, and RNNs, work by offering excellent feature extraction and generalization, along with a form of hierarchical representation learning. Such models add diagnostic and therapeutic value to gait analysis by offering important improvements in identifying subtle abnormalities in locomotion and supporting clinical decision-making.

3.2.1. GCN: Graph Convolutional Networks

Graph Convolutional Networks (GCNs) are a good fit for gait analysis because they process directly on graph-structured data, thus allowing for modeling complex relationships. In gait classification, GCNs represent human body structures as graphs where nodes are corresponding to key body segments or joints, and edges encode spatial and temporal relationships. By processing data through these graphs, GCNs capture both local and global dependencies and thus can identify abnormalities in gait, such as inconsistencies in joint movement and asymmetry.

One other important characteristic of GCNs is their flexibility in computing a variety of data formats, such as skeletal joint angles, motion markers, or accelerometer readings, rendering them suitable for multi-sensor configurations. Their capabilities of gathering information from its neighbors improve their ability in identifying slight changes in dynamics in gait. For the purposes of early diagnosis and tailored treatment planning in conditions such as musculoskeletal and neurological disorders, such capability makes GCNs useful tools.

3.2.2. ResNet

ResNet (Residual Network) solves the issues of training deep neural networks, like vanishing gradients, by providing shortcut connections that bypass certain layers. These connections simplify learning, focusing on residual mappings to allow the network to train deeper architectures with improved accuracy. ResNet is particularly effective in classifying normal and abnormal gait patterns from large datasets by extracting complex spatial and temporal relationships.

The ResNet-based gait classification model uses residual blocks and convolutional layers for hierarchical feature extraction. The model begins with an input layer that scales images and progressively deepens through convolutional layers, max-pooling, and batch normalization. Residual blocks preserve information from the input and avoid degradation in learning as the depth of the network increases. The model ends with Global Average Pooling and fully connected layers, culminating in a softmax layer for classification. This design is an extension of the ResNet-34 architecture, and deep hierarchical feature representations guarantee precise predictions.

A convolutional layer and 128 filters of size 3x3 are used to achieve higher resolution. This layer reduces the spatial dimension to 8x8, increasing the depth to 128.More remaining blocks, similar to the previous ones, are then added with 128 filters of size 3x3. This block increases the depth of the feature map while maintaining the 8x8 spatial dimension. Global Average Pooling is used to gather each feature map into a single value. This process results in a feature vector of size 128. This feature vector is then fed to a fully concatenated layer to produce a classification probability for normal and non-normal gaits, followed by a softmax activation function. This architecture is inspired by the ResNet-34 model, which includes jump connections and residual blocks to solve vanishing gradient problems and train deep neural networks. By gradually increasing the depth and complexity, the model learns a hierarchical representation of the input image and allows accurate predictions for normal and normal walking classification. We can look at the block diagram of the described ResNet model in Fig. 2.

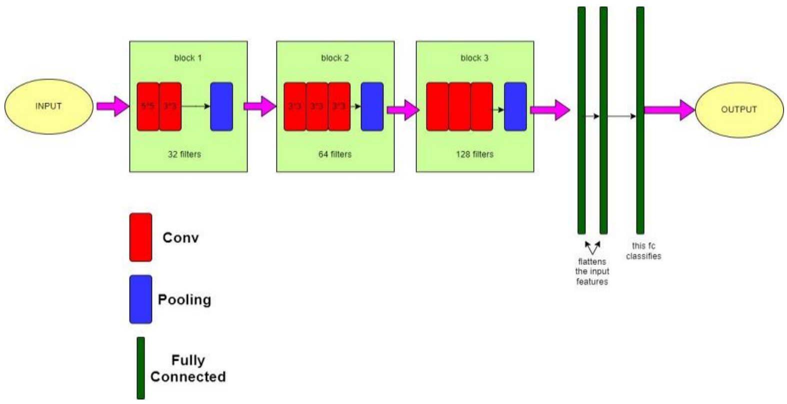

Fig. 2. Proposed ResNet Architecture and Parameters

4. RESULTS AND DISCUSSIONS :

This graph highlights the performance of different machine learning and deep learning models on the Kinect Gesture dataset, showcasing their accuracy and advancements over the years across various countries.

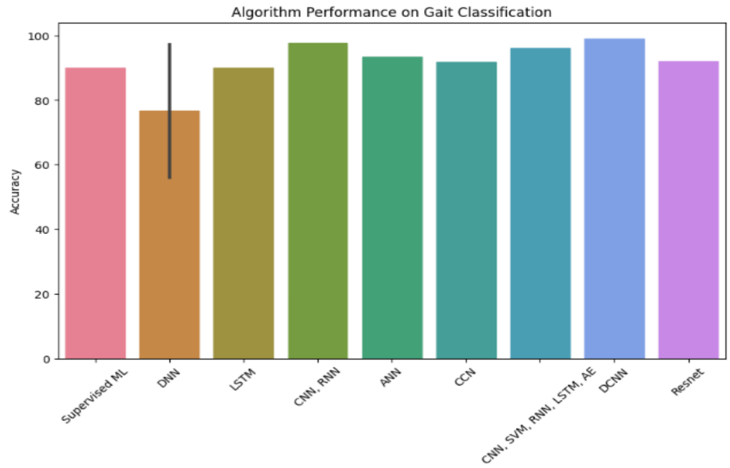

Fig. 3. Comparision of Various Models on Gait classification

The loss function graph in Fig. 4. illustrates the ResNet model's performance during training on the Kinect Gesture dataset, showing how the loss decreases as the model learns.

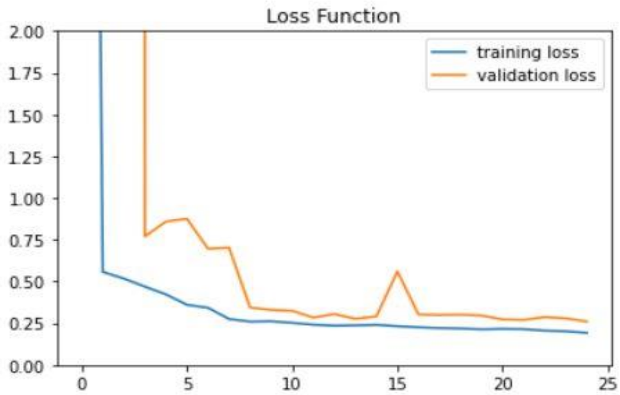

Fig. 4. Loss function of ResNet model on Microsoft Kinetic Gesture Dataset

The AUC and ROC curve collectively evaluate the ResNet model's classification performance on the Kinect Gesture dataset. The ROC curve visualizes the trade-off between sensitivity (TPR) and specificity (FPR), while the AUC quantifies the model's overall ability to distinguish between normal and abnormal gestures, with higher values indicating superior performance.

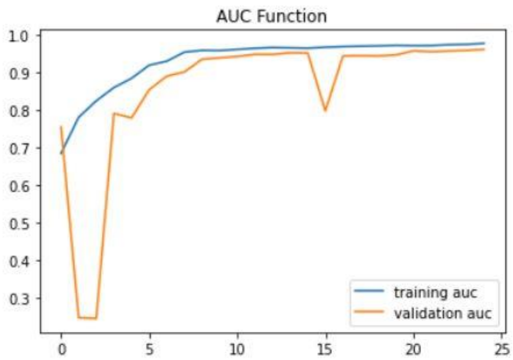

Fig. 5 AUC function of ResNet model

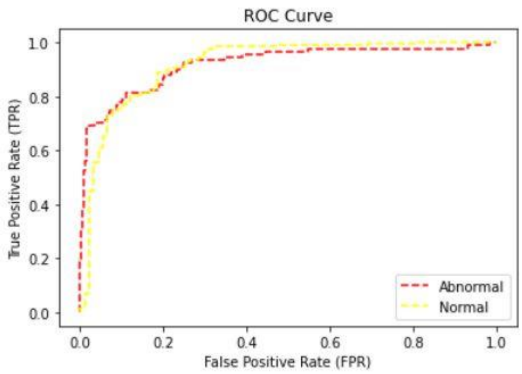

Fig. 6 ROC Curve of ResNet model

5. CONCLUSION :

In this paper, we used the ResNet algorithm to perform human motion analysis using the Microsoft Research Cambridge-12 Kinect gesture dataset. The dataset was totally complete in collecting sequences which captured body and limb positions with a total of 719,359 images in 594 sequences. Thus, this extensive data set allowed us to study human gestures more closely and analyze their behavior. The results of our analysis using the ResNet algorithm were promising, as it was able to yield an accuracy of 92%. This is an indicator that ResNet can well classify and recognize human gestures based on anatomical position. Renowned for its deep residual learning architecture, the ResNet algorithm was able to extract meaningful features and provide reliable predictions in human motion analysis. The availability of large datasets such as the Microsoft Research Cambridge-12 Kinect gesture dataset has greatly contributed to research advances in human motion analysis. These datasets allow complex machine learning algorithms to be developed and tested for accuracy in gesture recognition and gait analysis and confirmed. In conclusion, our research proves the capability of ResNet algorithm in human motion analysis and gives some useful recommendations for gesture recognition and gait analysis improvement.

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