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# PREDICTION AND CLASSIFICATION OF GAIT DISORDERS BASED ON HYBRID DEEP LEARNING TECHNIQUE

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**Abstract ---** Human gait is analyzed based on their walking patterns. Gait disorders can be diagnosed early with the help of fast-growing technologies. By using gait features, Parkinson disease, hemiplegic disease, and neuropathic disease can be identified. To obtain a high performance of gait analysis and classification, deep-learning techniques are presented. In this paper, Convolution Neural Network (CNN) with Long Short-Term Memory (LSTM) is proposed. The Chinese Academy of Sciences (CASIA) dataset is used to analyse the different types of gait disorders. A set of features is trained with the data from this dataset to reduce training time and remove irrelevant and noisy data. The lean and ramp angle features extracted from the dataset are considered as the prominent features for gait analysis in this work. As a result, the proposed method is capable of accurately classifying disorders and requires less computational time. In this study, we compare the experimental results with those of other machine learning algorithms. In order to assess the proposed system's performance, performance metrics such as F1 score, precision, accuracy, and recall are used. Due to its increased performance, the proposed system was able to surpass other techniques of a similar nature.

**Keywords ---** convolution neural network, CASIA dataset, long short-term memory, machine learning algorithms.

## 1 Introduction

Gait analysis is performed to know the walking ability of human beings. People with neurological diseases are affected by their locomotor ability. Gait analysis helps to diagnoses the patient neuromuscular condition to plan for minimal treatment, and examine rehabilitation outcomes [1]. In gait study, a person's movement identifies their particular walking style, which means it may be used to classify them. Gait identification is a biometric method for determining biological and behavioural characteristics. Methods in gait identification technology are separated into two types: holistic-based technique and model-based. The holistic method focuses on extracting predictive motion-based characteristics, while a 3D gait model is constructed using an object-based approach that separates body parts [2]. Gait analysis is widely used to endorse and standardize analysts', doctors', and therapists' conclusions after evaluating gait anomalies and recognizing improvements attributable to orthopaedic or physiotherapeutic treatments to avoid, detect, or recover a lack of mobility due to (gait) impairments [3].

A sick or abnormal gait differs from the normal pattern. A number of factors can contribute to this deviation, including most commonly neuromuscular disorder, hemiplegia, and aging. Gait may be affected differently by various diseases and factors [4]. Neurological disorders are typically diagnosed by neurological tests, although experiments have found that gait patterns can help in the detection of neurological diseases. "Natural gait" refers to a person's gait cycle that is free of deformities. Pathological gait (or abnormal gait) is an impaired gait pattern caused by nervous fatigue, deformities, lack of muscle control, and pain [5]. Parkinson's gait disease is a neurological dysfunction in which degeneration in the substantia nigra of the midbrain of dopamine neurons, resulting in gradual motor system degeneration. Resting tremors, trunk and limb weakness, bradykinesia (slowness of movement), akinesia (paralysis), and postural abnormalities are all symptoms of Parkinson's disease, the second most common neurological condition [6].

Gait features can be obtained in two ways for any human: cameras and sensors. In a single day, surveillance cameras will film tens of thousands of people in a public space, many of which have the same profile. Sensors, such as accelerometers and gyros are another method for constructing a gait model. The sensor devices are attached with the human body, and the sensor measurements are used to conduct gait analysis [7]. In inertia-based strategies, gyroscope and accelerometer inertial sensors are used to record the inertial data generated by a walking body. Since they record gait dynamics in a general way, inertial data has been found to be useful for extracting walking characteristics [8]. These characteristics can be obtained and used in the evaluation of gait parameters and related treatment efforts if a specific quantitative features subset is used to describe gait. The defining characteristics may show hidden similarities and variations in gait parameters [9].

Deep learning techniques have largely succeeded in several challenging research areas, including image identification, natural language processing, and activity recognition. In recent years, deep learning methods have gained popularity for automatically extracting a wide range of features from a variety of data types. One method that they employ to train their models using these methods is to transform 1-D signals into images and then extract features from the images [10]. Deep learning models can be applied to complex data with minimal pre-processing and can produce quicker, more reliable results from datasets that are constantly increasing in volume and range, thanks to advances in machine learning technology. It opens up new possibilities for detecting, fusing, and classifying data from various multi-source, multi-sensor sources [11]. In this paper, the abnormalities of gait are analysed. There are various gait diseases are caused due to problems in nervous system. Some of the problems are Neuropathic gait, Parkinson’s gait, and hemiplegic gait. These diseases disrupt the normal life of human beings. Timely detection of these diseases is helpful for the persons who are suffered from these diseases. For prediction of these diseases CNN with LSTM is used which is a deep learning technique. The data from CASIA database is extracted to diagnose the diseases of gait.

The contributions of the work are as follows,

- ❖ The CNN with LSTM is efficiently implemented for gait analysis.

- ❖ The combination of two networks makes gait analysis easier, accuracy is increased and computation time is reduced. The proposed system is trained using extracted features of CASIA dataset. By fine-tuning the hyperparameters, CNN-LSTM performance is improved

.

Following this, Section 2 deals with the works related to gait analysis. The methodology and techniques used in the proposed work are described in Section 3. Results and discussion are discussed in Section 4 and conclusions are presented in Section 5.

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## 2 Literature review

Machine learning (ML) methods were used to assess the best combination of gait traits. The purpose of this test is to differentiate between Parkinson's disease patients and healthy controls [12]. Several machine learning (ML) techniques were used to define the right approach (random forest with recursive features elimination (RFE) and information gain) methodology with logistic regression and support vector machine demonstrated that custom-engineered instrumented insoles (Sport Sole) are used to derive reliable evaluations of essential gait factors (i.e., velocity, stride duration, and foot clearance) while running and walking tasks using support vector regression (SVR) techniques [13]. Furthermore, the models based on learning are resistant to inter-subject heterogeneity, eliminating the need for subject-specific training results. Researchers also studied about gait abnormality in recent years using deep learning. Developed an approach using leg Euler angle knowledge for diagnosing and classifying abnormal gait patterns based on a LSTM and Convolutional Neural Network (CNN) (LCWS net), with parameters connected to features being changed adaptively based on feedback from targets and optimization parameters. Explained how deep learning combined with non-invasive wearable sensors to find artificially induced gait changes without the existence of gait analyst or a medical professional. The aim of this technique is to look at gait symptoms irrespective of whether the patient has any neuromuscular function disorders [14].

To implement the HGR, binary patterns are optimized. Clothing and conditions that are view-invariant were considered. In MLOOP, binary patterns are extracted. Using MLOOP, features for histograms and horizontal widths were extracted, and then irrelevant features were removed using a reduction technique.

In order to implement HGR, optimal binary patterns are used. A view-invariant clothing and condition problem was considered. Binary patterns are extracted using MLOOP. In this study, to reduce the irrelevant features, MLOOP was used to extract histogram and horizontal width features. The experimental process is performed with two datasets [15]. [16] In this paper, we present a deep learning-based approach to HGR with various view invariants and cofactors. In this method, two pre-trained models were modified for feature extraction. A fuzzy entropy and skewness-based formulation is used to fuse and improve parallel approach-based features. Four datasets were used in the experiment, yielding accuracy rates of 99.8, 99.7, 93.3, and 92.2 percent, respectively. [17]. According to the results of a study on deep learning algorithms for cancer detection and diagnosis, the convolutional neural network (CNN) is one of the most widely used deep learning algorithms when it comes to deep learning and the analysis of medical images. [18]. [19] A convolutional neural network-based classification model was proposed to detect cases of melanoma with high accuracy. Data augmentation technique was used to improve performance by using the Efficient Net and VGG-19 architectures for image classification.

[20] An improved method for classifying tumours in MR images is presented using deep learning. First, to learn the structure of MR images and to extract robust features, a deep neural network is trained as a discriminator in a generative adversarial network (GAN). In order to distinguish three tumour classes, the entire deep network is trained as a classifier by replacing fully connected layers. Six layers and 1.7 million parameters make up the deep neural network classifier. [21] Human health can be diagnosed and monitored with the help of a gait analysis. Many current gait measurement techniques rely on specialists or expensive equipment. In order to measure gait parameters, a simple, inexpensive, quantitative technique is clearly needed. The proposed work focuses on investigating the feasibility of obtaining useful quantitative gait parameters from floor acceleration measurements as a function of footfall input. Accelerometers mounted under the floor measured the vertical acceleration of the floor during the study of 17 participants who walked along the hallway for 115 feet [22].

Gait can be used to identify people at a distance without interacting with the system since it is a biometric feature. The performance of gait recognition can be affected by a variety of factors, such as clothing, shoes, and walking surface. It is especially difficult to recognize gait from a cross-view since each viewpoint drastically changes the appearance of the walk of the individual. This paper presents a novel view-invariant gait representation based on the spatiotemporal motion characteristics of human walking [23]. Cardiovascular centers do not exist in rural areas. As a result, WHO reports that around 12 million people pass through the world each year. Cardiovascular disease risk is predicted using artificial intelligence classifiers. However, the ML model is susceptible to feature selection, attribute splitting, and imbalanced datasets prediction. Multi-class labels appear in most of the mass datasets, but the proportions of the classes vary [24]. Human recognition technology determines the people present in images in order to identify them. Achieving high accuracy rates and speed in automatic human recognition at night remains a challenge. This article develops a novel method that integrates face and gait analysis into TIR images for real-time human recognition at night in various walking scenarios. The purpose of this article is to develop a novel approach for enhancing real-time human recognition in TIR images at night under various walking scenarios that integrates gait and face analysis. Using this network, TIR images are optimized, more accurate features (face, gait, and body segment) of the person are detected, and PRM-Net classified the images for human recognition. [25].

In the 1990s, Human Gait Recognition (HGR) became a popular biometric method for security purposes. HGR evaluates the performance of a system in terms of covariate controls such as clothing and bag carrying. Additionally, HGR faces the challenge of recognizing objects from different perspectives. A novel fully automated method using deep learning is presented here for HGR under a variety of view angles. In order to extract features from the original video frames, a Densenet-201 CNN model is used, additional features from the extracted vector are reduced with a hybrid selection method, and finally recognition is achieved using supervised learning methods. [26]. Since longitudinal data can be used to track the progression of a disease such as AD, research has been limited to date due to a lack of patient data and short follow-up periods. In the absence of a large dataset, it is impossible to estimate the underlying disease progression model; therefore, a nonparametric supervised method is proposed. For training, longitudinal data of three years are utilized, whereas for validation, only the baseline visit's data are used. Two dense clusters representing MCI and AD subjects are extracted from the pre-processed train set after three years from the baseline visit [27]. The KNN algorithm varies the number of neighbours in each classification, k, in order to avoid overfitting or underfitting our data. As the model learns from only a small subset of neighbour samples with a small number of neighbours, the effect of noise becomes greater. In contrast to finding a general pattern, we observe a bias towards minor details in the data (overfitting) when outliers heavily influence the model. If k is large, however, a test sample will be classified to the target (under-fitting). When ignoring underlying training, a smaller k is more frequently used [28].

In this paper, the abnormalities of gait are analysed. There are various gait diseases are caused due to problems in nervous system. Some of the problems are Neuropathic gait, Parkinson’s gait, and hemiplegic gait. These diseases disrupt the normal life of human beings. Timely detection of these diseases is helpful for the persons who are suffered from these diseases. For prediction of these diseases CNN with LSTM is used which is a deep learning technique. The data from CASIA database is extracted to diagnose the diseases of gait.

The contributions of the work are as follows,

- The CNN with LSTM is efficiently implemented for gait analysis. The combination of two networks makes gait analysis easier, accuracy is increased and computation time is reduced.
- The proposed system is trained using extracted features of CASIA dataset. The performance of the CNN-LSTM is improved by fine-tuning the hyper parameters

## 3 Methodology

This section explains the classification of gait disorders using various approaches and techniques. The architecture of gait analysis includes pre-processing, extraction of features, and classification. In the process of abnormal gait classification, we have to train the model. The proposed methodology for gait prediction and gait disorders is shown in Figure 1.

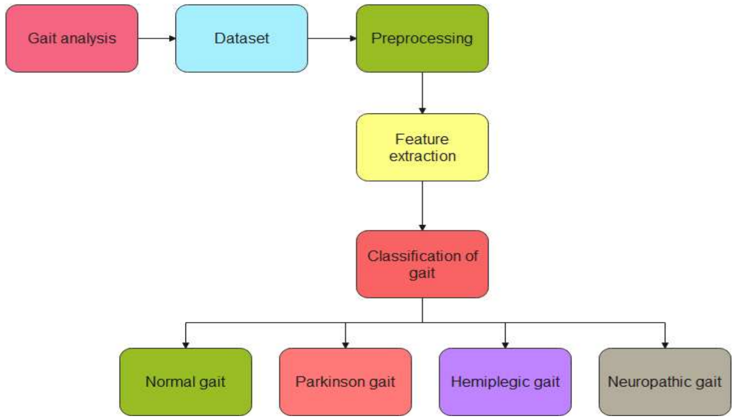



**Figure 1**- The proposed methodology for gait prediction and gait disorders

### 3.1 Dataset

This study uses a dataset from the CASIA. In order to recognize gaits, the Institute of Automation, provides the CASIA gait Database. It is a large Multiview gait database. A separate consideration is made for three variations, namely changes in view angle, clothing, and carrying condition. Additionally, human silhouettes are extracted from video files. The gait cycle of a person is shown in Figure 2.

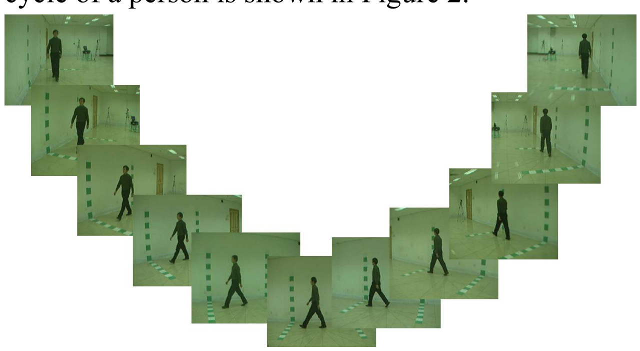


**Figure 2 -** Gait cycle of a person

### 3.2 Gait analysis

Gait analysis is the method of evaluating a person's walking pattern, assessing body motions, body dynamics, and muscle function. Hemiplegic gait, Parkinson's gait, and neuropathic gait are examples of gait abnormalities. The LSTM with CNN neural network is used to identify and classify the gait disorders. Recent developments in the deep learning have inspired scientists to apply this approach to the problem of irregular gait classification. Variety of experiments including inertial analysis, including irregular and natural gait analysis, fall identification, patient recovery and care, and disease analysis of the nervous system. For abnormal gait analysis, the proposed network is efficiently trained and built to classify four classes of gait such as,

- Class A- Normal gait
- Class B- Parkinson gait

- Class C- Hemiplegic gait
- Class D- Neuropathic gait

One complete gait cycle has been extracted as a feature vector. Feature vectors are calculated by calculating the maximum, average, and minimum lean angles from the center of gravity to the line from head to hip. In the first and second halves of the gait cycle, the angle between ground truth and heel-to-toe line for the left leg and right leg is measured.. We detect normal or abnormal gait based on the lean angle and ramp angle of the subjects in each gait cycle. A contour extraction method is used to calculate the lean angle from the images of the dataset. Lean angle is calculated between the head and hip. A ramp angle is calculated using the H-T-H-T algorithm (heel to toe and heel to toe). From the heel and toe of the foot, the ramp angle of each leg has been calculated. During the mid-stance phase of the gait cycle, in each gait sequence, the silhouette images are subtracted from the background, and the feature vectors lean angle and ramp angle are calculated based on each silhouette image. Each gait cycle is analysed using a significant feature vector based on the gait patterns. A hybrid algorithm combines different approaches to classify normal and abnormal gaits and increase classification accuracy. Classifiers are trained using feature vectors extracted from walking sequences of an individual. As a classification parameter, both the ramp angle and lean angle are considered.

The normal walking pattern of human beings indicates natural gait cycles and it allows at least one foot touch the ground for one gait cycle. Lean angle and ramp angle are measured in order to determine normal gait. An individual is considered normal when their lean angle is between 1°-8° and their ramp angle is between 5°-25°. The lean angle samples of three normal gait cycles are illustrated in Table 1.

**Table 1.** Lean angle for normal gait cycle

| **Lean angle** | **Gait cycle 1** | **Gait cycle 2** | **Gait cycle 3** |
|---|---|---|---|
| Maximum | 5° | 7° | 6° |
| Average | 3° | 5° | 4° |
| Minimum | 2° | 2° | 3° |

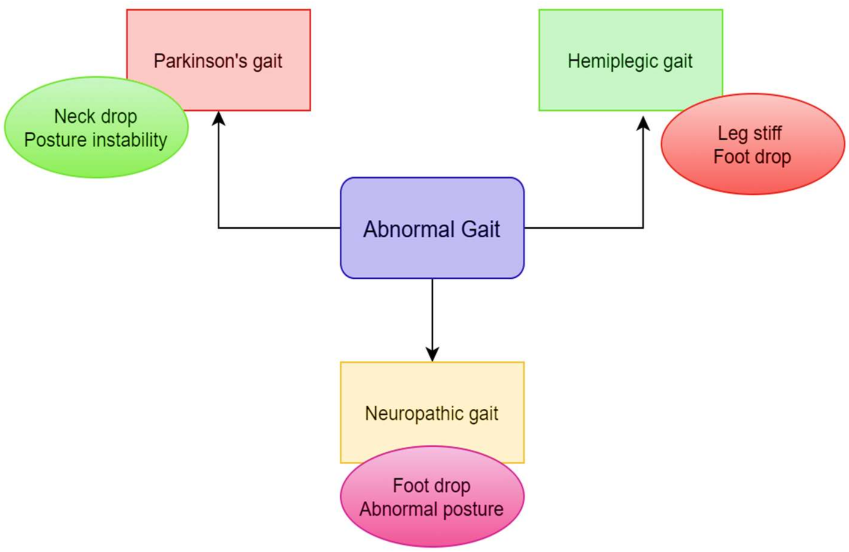
The maximum ramp angle is between 1°- 8°, and the minimum ramp angle is between 5°-25°for the normal gait cycle. The ramp angle samples of three normal gait cycles are illustrated in table 2.

**Table 2.** Ramp angle for normal gait cycle

| **Ramp angle** | **Gait cycle 1** | **Gait cycle 2** | **Gait cycle 3** |
|---|---|---|---|
| Maximum | 21° | 23° | 20° |
| Minimum | 6° | 8° | 4° |

### 3.2.2 Abnormal gait

Human beings with neuromuscular disorders experience an abnormal gait cycle or normal walking difficulties. Measurements of the lean angle and ramp angle are performed on three people in order to test abnormal gait. When a gait is abnormal, its lean angle is between 30° and 55° and its maximum ramp angle is between 20° and 35°, and its minimum ramp angle is between 0° and 6°.The lean angle and ramp angle samples of three abnormal gait cycles are shown in Tables 3 and 4. The classifications of abnormal gait disorders are illustrated in Figure




3.

**Figure 3** - Classification of abnormal gait disorders

**Table 3.** Lean angle of abnormal gait cycles

| **Lean Angle** | **Gait Cycle** | | |
|---|---|---|---|
| | **1st Cycle** | **2nd Cycle** | **3rd Cycle** |
| Maximum | 51° | 48° | 53° |
| Average | 39° | 41° | 44° |
| Minimum | 43° | 38° | 40° |

**Table 4.** An abnormal gait cycle's ramp angle for gait phase

| Phase of gait | Foot | Ramp angle | Gait Cycle | | |
|---|---|---|---|---|---|
| | | | **1st cycle** | **2nd cycle** | **3rd cycle** |
| Stance Phase | Left | Maximum | 21° | 25° | 36° |
| | | Minimum | 5° | 3° | 6° |
| | Right | Maximum | -6° | 25° | 18° |
| | | Minimum | -26° | -8° | 23° |
| Swing Phase | Left | Maximum | 36° | 25° | 26° |
| | | Minimum | 27° | 7° | 5° |
| | Right | Maximum | 31° | 29° | 3° |
| | | Minimum | 2° | -13° | 8° |

### 3.2.3 Parkinson gait

People with Parkinson diseases usually take small, shuffling steps. They might have difficulty picking up their feet. This abnormal gait cycle indicates one of several motor symptoms that are the hallmarks of Slowness of movement and tremors are common symptoms of Parkinson's disease. Posture control loss is the main symptom of Parkinson gait disorder. For Parkinson's disease, the lean angle is 45°-55°, the maximum ramp angle is 30°-35°, and the minimum ramp angle is 2°-6°.

### 3.2.4 Hemiplegic gait

The hemiplegic gait is typically caused by a disruption to the corticospinal tract, which is above the medulla. The hip and knee swing are impaired during hemiplegic walking with leg circumduction. Those with hemiplegia exhibit spastic flexion of the upper limb and spastic extension of the lower limb. The lean angle is between 38°-45°, maximum ramp angle is 25°-30° and minimum ramp angle is 0°-6° for Hemiplegic disease.

### 3.2.5 Neuropathic gait

Persons with Neuropathic gait faces very slow walking pattern, there are no knee extension movements while walking sequence. Foot slaps, ankle dorsiflexion, hip flexion, and knee extension are the main symptoms. The lean angle is between 30°-38°, maximum ramp angle is 20°-25° and minimum ramp angle is 0°-6° for Neuropathic disease. The lean angle of

Parkinson, Hemiplegic and Neuropathic gait are illustrated in Table 5. The ramp angles of three gait disorders are given in Table 6.

**Table 5**. The lean angle of Parkinson, Hemiplegic and Neuropathic gait

| **Lean angle** | **Gait** | | |
|---|---|---|---|
| | **Parkinson** | **Hemiplegic** | **Neuropathic** |
| Maximum | 53° | 43° | 33° |
| Average | 48° | 27° | 25° |
| Minimum | 3° | 1° | 2° |

**Table 6.** The ramp angle of Parkinson, Hemiplegic and Neuropathic gait

| **Phase of gait** | **Foot** | **Ramp angle** | **Parkinson gait** | **Hemiplegic gait** | **Neuropathic gait** |
|---|---|---|---|---|---|
| Stance Phase | Left | Maximum | 35° | 25° | 21° |
| | | Minimum | 6° | 2° | 4° |
| | Right | Maximum | 26° | 21° | -8° |
| | | Minimum | -3° | -6° | -23° |
| Swing Phase | Left | Maximum | 33° | 22° | 24° |
| | | Minimum | 5° | 7° | 5° |
| | Right | Maximum | 29° | 26° | -3° |
| | | Minimum | 34° | -13° | -8° |

### 3.3 CNN-LSTM network

In the proposed work, CNN is combined with LSTM to analyse the gait disorders. The lean and ramp angle features are taken to train the proposed network model. The architecture of CNN-LSTM model is shown in Figure 4.

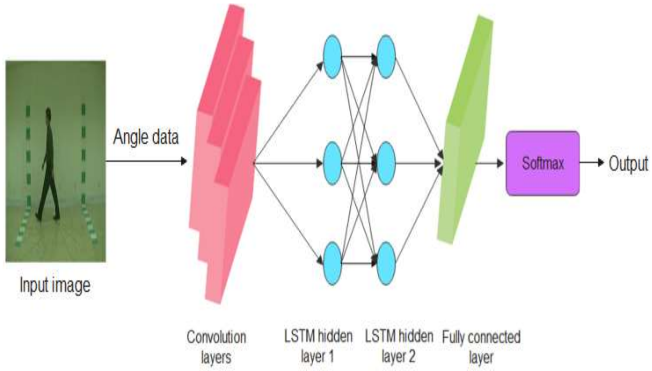



**Figure 4 -** Architecture of CNN-LSTM network

### 3.3.1 Convolutional Neural Network

The convolutional neural network comprises of convolution layers that takes the input sequences of the gait data. The lean and ramp angle are the features that helps to classify the gait disorders. These features are given as input to the convolution layer of the network. The convolution layer performs the convolution operation on gait data. The gait features and their weights are expressed in equations (1) and (2)

$$I_g = I_{1,2,3.....n} \quad (1)$$

$$W_g = W_{1,2,3.....n} \quad (2)$$

where$I_g$ indicates the input value, and $W_g$ denotes the weight values. Multiply the inputs with the arbitrarily chosen weight vectors and then add them up.

$$K = \sum_{g-1}^{n} I_g W_g \quad (3)$$

where K denotes the summed value. Determine the activation function.

$$AF_g = R_g(\sum_{g-1}^{n} I_g W_g) \quad (4)$$

$$R_g = \exp(-I_g^2) \quad (5)$$

$AF_g$specifies the activation function, whereas $R_g$ specifies the exponential of $I_g$. The weight values are optimized utilizing the Adam optimization algorithm.

### 3.3.2 Long Short-Term Memory

The LSTM model is one of their current neural networks that learn order dependency in sequence prediction problems. In this work, the gait data from the convolution layer are input to the LSTM layer. The input gate, output gate, and forgetting gate are added to the neurons in the LSTM model. There are 128 hidden units in the hidden layer. Hidden layers are determined using a hyperparameter tuning method. Rectified linear units (ReLUs) are used in the hidden layer as a non-linear activation function. This helps to alleviate the problem of vanishing states and error gradients. ReLU has been shown to be more effective and capable of speeding up the entire training phase.

The following is the statistical equation for LSTM (Gao et al., 2019).
Input gate:

$$i_t = \sigma(W_i[h_{t-1}, x_t] + b_i) \quad (6)$$

$$\tilde{C}_t = \tanh\,(W_C[h_{t-1}, x_t] + b_C \quad (7)$$

Forget gate:

$$f_t = \sigma(W_f[h_{t-1}, x_t] + b_f) \quad (8)$$

Cell state:

$$C_t = f_t * C_{t-1} + i_t * \tilde{C}_t \quad (9)$$

Output gate:

$$o_t = \sigma(W_o[h_{t-1}, x_t + b_o) \quad (10)$$

Finally, output of LSTM unit is:

$$h_t = o_t * \tanh(C_t) \quad (11)$$

The learnable parameters in each gate are bias vector b and weight matrix W of the above equation; σ(x) is the sigmoid function; and *symbolises dot output. Input gates select how much input data is stored, forget gates describe how much previous data is forgotten, and output gates indicate how much data will be output. The input layer, hidden layer, fully connected layer, and softmax layer are the layers in the CNN-LSTM model. The initial learning rate was fixed to 0.001, the mini batch size was fixed to 40, and the epochs were set to 100. The LSTM network's weights and preferences are chosen at random. The flow of classification of gait disorders are shown in Figure 4. Here, the classification algorithm starts processing the trained features and conditional features. The lean and ramp angle with conditional features for normal gait cycle and abnormal gait cycle are considered for classification. The algorithm compares the angle values with conditional features. If condition is satisfied it classifies the class, if the condition is not satisfied then starts the next iteration and so on. Finally, the gait disorders are classified by this process.

### 3.3.3 CNN-LSTM

CNN-LSTM is used instead of other ANN architectures since it can extract information spatially and temporally. The CNN-LSTM combines the strengths of CNN and LSTM. In visual classification tasks, CNN has demonstrated outstanding performance. The LSTM, on the other hand, is a type of recurrent neural network (RNN) that excels at tasks involving sequential data. The LSTM architecture is superior to other RNN architectures because it can learn long-term dependencies and eliminate unwanted features. LSTM networks are ideal for processing time-series data, such as gait data sequences, where order is crucial.
CNN-LSTM has been applied to a variety of problems across several domains.

CNN-LSTM models work by passing images through convolution layers, resulting in a 1D array with the features obtained. Input to the LSTM layer is derived from repeating this process for all the images in the time set. In image datasets containing both spatial and temporal information, CNN-LSTM architectures performed better than LSTMs and CNNs alone. To extract features, CNNs are used, followed by LSTMs to predict sequences. To convert the 3D output from the convolution layer to a 1D vector, a flattening layer was added just after the CNN block. After each LSTM output was produced, it was concatenated and passed through a dense layer.

. CNN-LSTMs combine the strengths of CNN and LSTM architectures, making them ideal for gait analysis

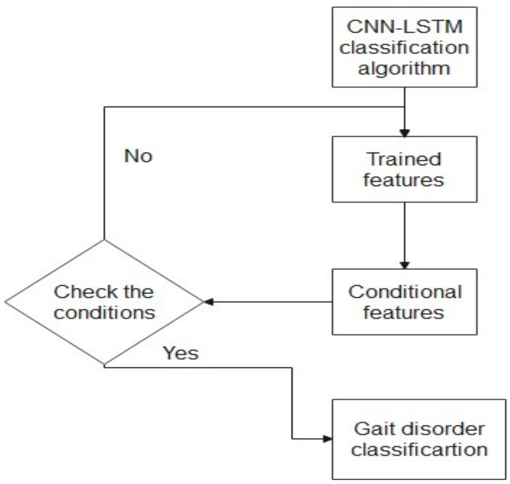



**Fig. 5.** Flowchart for classification of gait disorders

## 4 Results and Discussion

The performance of the proposed approach is discussed in this section. The CNN-LSTM, a deep learning algorithm for gait disease classification, is used in this study. To distinguish different gait disorders, the deep learning system employs a deep neural network that takes the lean and ramp angle features and process it to classify the disorders of gait. For classification, the CNN with LSTM is constructed. Deep learning uses a higher-level learning algorithm to work with large number of hidden layers, resulting in a greater learning capability and higher classification performance. In this dataset, 80% of the data is used to train the model, and 20% of the data is used to test the modelTraining datasets are used to build the model, and testing datasets are used to test the classifier's ability to detect new samples. Four performance measures that are precision, f1 score, accuracy, and recall are used to assess the performance of the classifiers. The efficiency of our proposed CNN-LSTM was compared to that of other algorithms which are Logistic Regression, Random Forest, Gradient Boosted Decision Tree and Support Vector Machine. These algorithms are the supervised machine learning algorithms widely used for many problems. Logistic regression is a special form of regression that is used for classification rather than estimation. It has a low variance due to its simple operation structure. Machine learning uses random forests to solve problems related to regression and classification. An ensemble learning technique is used to provide solutions to complex problems by combining many classifiers. Both Gradient Boosting and AdaBoost predicts a target label using a decision tree ensemble. SVM used for classification, regression and outliers' detection. Numerous practical problems can be solved with it, both linear and nonlinear methods.

**Table 7.** List of best hyperparameters of LSTM

| **Hyper parameters** | **Value** |
|---|---|
| No. of Hidden layers | 2 |
| No. of Hidden units | 128 |
| Activation function | ReLu |
| Learning rate | 0.001 |
| Optimizer | Adam |

The best hyperparameters of the LSTM network is shown in the above Table 7. Using the Adam optimization algorithm, the momentum component is integrated with the Adagrad optimization algorithm to provide fine-grained control over the decay of the learning rate, as well as allow for adaptive adjustment of the learning rate during training without the need to manually fix weight decay.

### 4.1 Number of hidden layers

Network capacity is determined by the number of hidden layers in the network. The number of hidden layers varies from 1 to 3. The network's output is evaluated using hidden layers ranging from 1 to 3.

**Table 8.** Metrics for CNN-LSTM based on 1, 2 and 3 hidden layers

| **Metrics** | **No. of hidden layers** | | |
|---|---|---|---|
| | **1** | **2** | **3** |
| Accuracy | 0.95 | 0.99 | 0.84 |
| Precision | 0.88 | 0.96 | 0.88 |
| Recall | 0.83 | 0.91 | 0.91 |
| F1 Score | 0.88 | 0.84 | 0.85 |

The accuracy and precision of the network is high when there is two layers in the network as shown in Figure 6. Table 8 illustrates the best network for this work, which has three hidden layers... When the number of layers is 3, the proposed model performs well and the accuracy and precision are high compared to other layers shown in Figure 7, because when the layers are below 2 the model is under fitting and when more than 2 layers the model is overfitting.

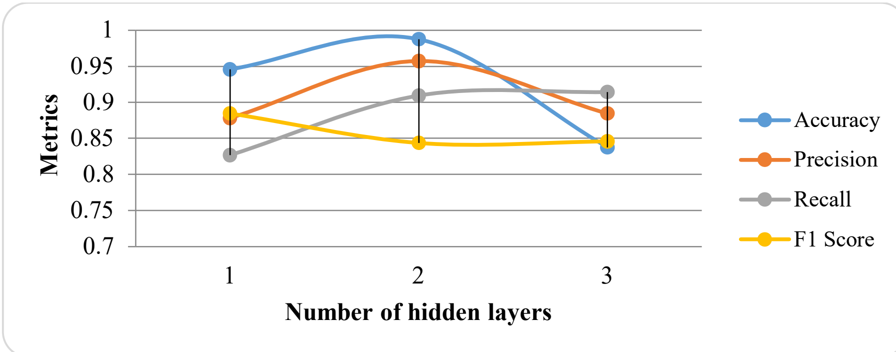



**Fig. 6.** CNN-LSTM performance measures based on 1, 2, and 3 hidden layers

### 4.2 Number of hidden units

In this work, several numbers of hidden units are used and altered in each layer. Following that, we analyze the performance of the LSTM classifier with various hidden unit counts. When the unit in each layer is 128, the proposed method has the highest accuracy and precision which is presented in Table 9.

**Table 9**. Metrics for CNN-LSTM based on 32, 64, 128 and 256 hidden layers

| **Metrics** | **No. of hidden layers** | | | |
|---|---|---|---|---|
| | **32** | **64** | **128** | **256** |
| Accuracy | 0.84 | 0.96 | 0.99 | 0.88 |
| Precision | 0.85 | 0.84 | 0.94 | 0.90 |
| Recall | 0.91 | 0.91 | 0.91 | 0.85 |
| F1 Score | 0.85 | 0.81 | 0.88 | 0.89 |

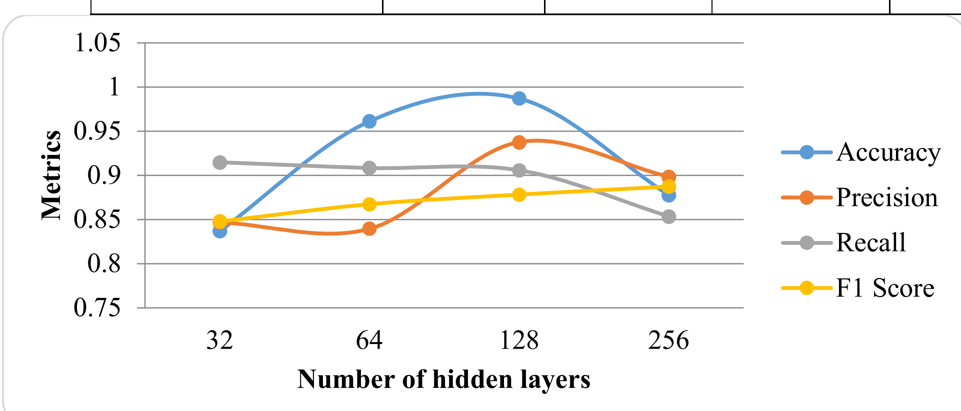



**Fig. 7.** CNN-LSTM Metrics based on 32, 64, 128 and 256 hidden layers

When the number of hidden units in the LSTM layer is 128, the model performs well in terms of accuracy and precision.

### 4.2.1 Performance evaluation metrics

Performance metrics used to compare algorithms include accuracy, precision, recall, and F1 score.

Accuracy defines the percentage of the total number of exact classifications.

$$\text{Accuracy} = \frac{\text{TP+TN}}{\text{TP+TN+FP+FN}} \quad (12)$$

Precision is the total of right classifications with the total of improper classifications.

$$\text{Precision} = \frac{\text{TP}}{\text{TP+FP}} \quad (13)$$

A recall measure examines the number of accurate classifications in comparison to the number of missed entries.

$$\text{Recall} = \frac{\text{TP}}{\text{TP+FN}} \quad (14)$$

F1-score measures precision and recall harmonically.

$$\text{F1 score} = \frac{\text{Precision.Recall}}{\text{Precision+Rec}} \quad (15)$$

**Table 10.** Accuracy Precision comparison of CNN - LSTM with RF, GBDT, SVM and LR

| **Dataset** | **Algorithms** | | | | |
|---|---|---|---|---|---|
| | **CNN - LSTM** | **RF** | **GBDT** | **SVM** | **LR** |
| CASIA - A | 97.32 % | 87.01 % | 83.25 % | 90.90 % | 96.88 % |
| CASIA - B | 98.95 % | 91.50 % | 93.88 % | 95.73 % | 90.56 % |
| CASIA - C | 86.98 % | 70.34 % | 81.90 % | 92.92 % | 88.90 % |

The accuracy of the proposed work is compared with the other algorithms such as RF, SVM, LR, and GBDT on different dataset such as CASIA-A, CASIA-B and CASIA-C that is shown in Table 10. The proposed algorithm obtains high accuracy of 97.32 %and 98.95 % on CASIA-A and CASIA-B respectively and SVM obtains high accuracy of 92.92 % on CASIA-C dataset is shown in Figure 8.

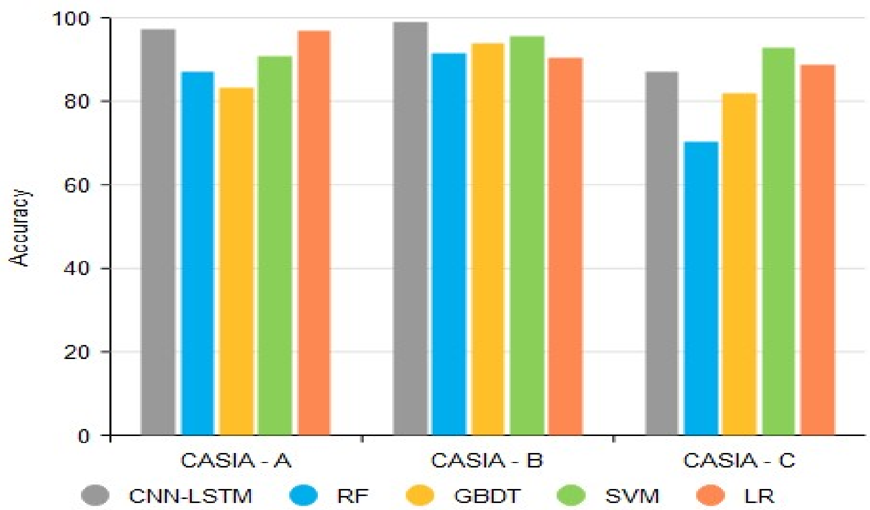



**Fig. 8.** Accuracy Precision comparison of CNN - LSTM with RF, GBDT, SVM and LR

**Table 11.** Precision comparison of CNN - LSTM with RF, GBDT, SVM and LR

| **Dataset** | **Algorithms** | | | | |
|---|---|---|---|---|---|
| | **CNN-LSTM** | **RF** | **GBDT** | **SVM** | **LR** |
| CASIA - A | 96.35 % | 89.58 % | 90.18 % | 93.87 % | 89.89 % |
| CASIA - B | 93.76 % | 76.89 % | 79.39 % | 89.93 % | 84.90 % |
| CASIA - C | 89.54 % | 91.34 % | 79.80 % | 90.09 % | 89.41 % |

In Table 11, precision of the proposed work is compared with the other algorithms such as RF, SVM, LR, and GBDT on different dataset such as CASIA-A, CASIA-B and CASIA-C. The proposed algorithm obtains high precision of 96.35 %and 93.76 % on CASIA-A and CASIA-B respectively and RF obtains high precision of 91.34 % on CASIA-C dataset is shown in Figure 9.

**Table 12**. Recall comparison of CNN - LSTM with RF, GBDT, SVM and LR

| **Dataset** | **Algorithms** | | | | |
|---|---|---|---|---|---|
| | **CNN-LSTM** | **RF** | **GBDT** | **SVM** | **LR** |
| CASIA - A | 89.31% | 96.99 % | 91.66 % | 93.34 % | 90.89 % |
| CASIA - B | 88.96 % | 78.73 % | 83.38 % | 92.10 % | 93.40 % |
| CASIA - C | 87.51 % | 95.38 % | 73.93 % | 76.33 % | 81.90 % |

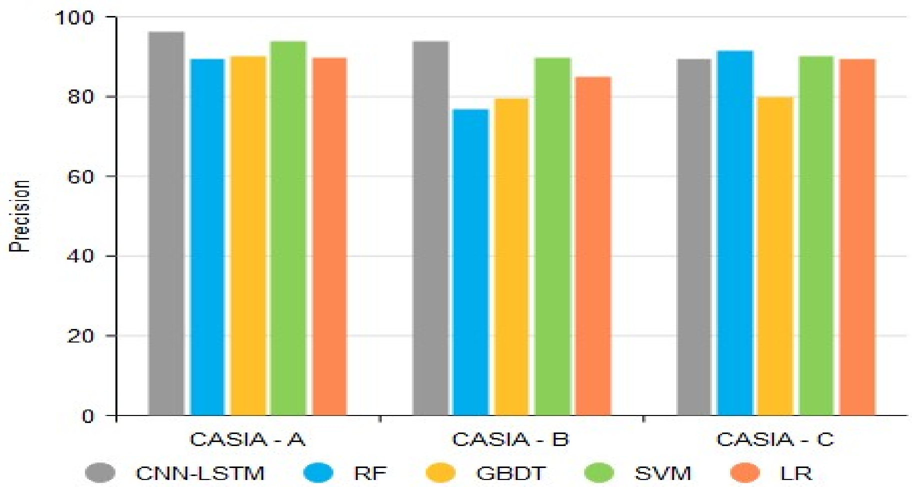



**Fig. 9.** Precision comparison of CNN - LSTM with RF, GBDT, SVM and LR

The recall of the proposed work is compared with the other algorithms such as RF, SVM, LR, and GBDT on different dataset such as CASIA-A, CASIA-B and CASIA-C that is shown in table 12. The proposed RF algorithm obtains high recall of 96.99 % and 95.38 % on CASIA – A and CASIA – C respectively and LR obtains high accuracy on CASIA-B dataset is shown in Figure 10.

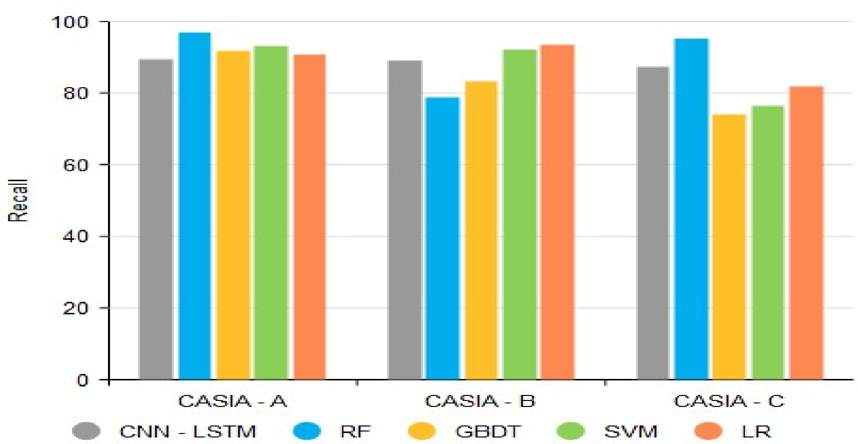



**Fig. 10.** Recall comparison of CNN - LSTM with RF, GBDT, SVM and LR

**Table 13**. F1 score comparison of CNN - LSTM with RF, GBDT, SVM and LR

| Dataset | Algorithms | | | | |
|---|---|---|---|---|---|
| | **CNN-LSTM** | **RF** | **GBDT** | **SVM** | **LR** |
| CASIA – A | 92.54 % | 83.58 % | 92.26 % | 85.77 % | 90.87 % |
| CASIA – B | 90.36 % | 79.53 % | 81.08 % | 90.34 % | 86.90 % |
| CASIA – C | 95.39 % | 79.54 % | 83.23 % | 76.76 % | 81.64 % |

In Table 13, the F1 score of the proposed work is compared with the other algorithms such as RF, SVM, LR, and GBDT. The proposed algorithm obtains high F1 score of 92.54 % on CASIA-A, 90.36 % on CASIA-B and 95.39 % on CASIA-C dataset is shown in Figure 11.

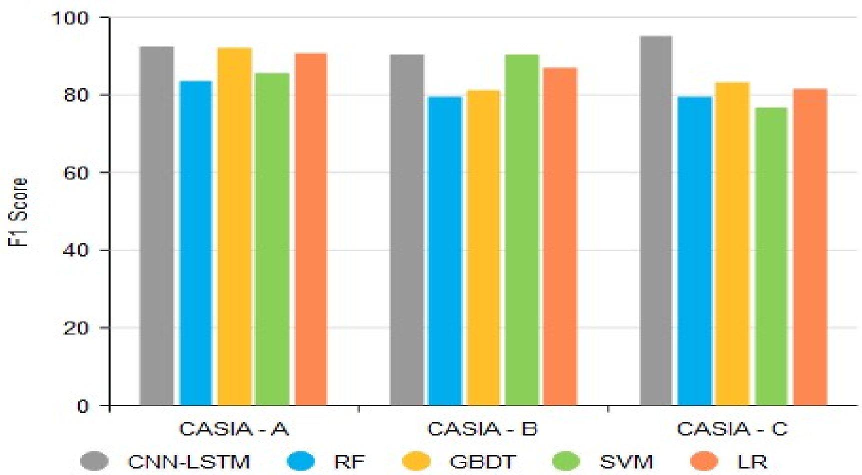



**Fig. 11.** F1 score comparison of CNN-LSTM with RF, SVM, LR, and GBDT

## 5 Conclusion

Abnormal gait analysis is critical in the medical field. Using deep neural network technology, CNN-LSTM is proposed. The proposed algorithm predicts and classifies the types of abnormal gait with the highest accuracy. The combination of CNN with LSTM outperforms the other state-of-art algorithms. Using the two networks together results in a high-performing algorithm that does not require the complex process of selecting optimal features for classification. By this method, the training time of the model is reduced, and the accuracy of the classification model is increased. The computed results proved that a combination of CNN and LSTM provides the highest recognition rate as compared with individual CNN or the LSTM models. The performance of the proposed system is assessed with the metrics such as F1 score, accuracy, recall and precision. The proposed CNN-LSTM algorithm obtains high accuracy of 97.32 % and 98.95 % on CASIA-A and CASIA-B respectively and precision of96.35 % and 93.76% on CASIA-A and CASIA-B respectively and F1 score of 92.54 % on CASIA-A, 90.36% on CASIA-B and 95.39 % on CASIA-C dataset respectively. In addition, a further study should examine the influences of older people and the different gait patterns of different age groups. The pre-training of convolutional networks could also benefit from transfer learning.

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