Enhancing fall detection and classification using Jarratt-butterfly optimization algorithm with deep learning

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Article Info

Article history:

Received Apr 6, 2024
Revised Nov 3, 2024
Accepted Nov 14, 2024

Keywords:

Computer vision
Deep learning
Fall detection
Machine learning
Metaheuristics

ABSTRACT

Falls pose significant risk to the health and safety of individuals, specifically for vulnerable populations as the elderly and those with specific medical conditions. The repercussions of falls can be severe, leading to injuries, loss of independence, and increased healthcare costs. Consequently, the development of effective fall detection systems is crucial for providing timely assistance and enhancing the overall well-being of affected individuals. Recent advancements in deep learning (DL) have opened new avenues for automating fall detection through the analysis of sensor data and video footage. DL algorithms are especially well-suited for this task because they can automatically learn complex features and patterns from raw data, eliminating the need for extensive manual feature engineering. This article introduces a novel approach to fall detection and classification, termed the fall detection and classification using Jarratt-butterfly optimization algorithm with deep learning (FDC-JBOADL) algorithm. The FDC-JBOADL technique employs a median filtering (MF) method to mitigate noise and utilizes the EfficientNet model for robust feature extraction, capturing both motion patterns and appearance characteristics of individuals. Furthermore, the classification of fall events is achieved through a long short-term memory (LSTM) classifier, with hyperparameter optimization facilitated by Jarratt-butterfly optimization algorithm (JBOA). Through a comprehensive series of experiments, the efficacy of FDC-JBOADL technique is validated, demonstrating superior performance compared to existing methodologies in the domain of fall detection.

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1. INTRODUCTION

The increasing aging of the population, particularly in developing nations, poses a significant challenge to the sustainability of medical treatments [1]. The proportion of people of working age (15 to 64) among the total population in European nations is projected to decline from 65.16% in 2016 to 56.15% by 2070, while life expectancy at birth is anticipated to rise by an additional 7 years for both women and men over the same timeframe [2]. In this instance, falls have been a significant cause of loss of autonomy and accidents among the elderly. The World Health Organization (WHO) research indicates that the annual fall rate for those aged 64 to 70 is around 28 to 35% and 32 to 40%, respectively [3]. Despite the lack of significant injuries, 47% of individuals who fall are unable to rise alone post-fall [4]. Moreover, prolonged periods of lying on the ground prior to falling are significantly associated with comorbidities and pressure sores, which increase the likelihood of mortality within six months to 50% [5]. From this viewpoint, prompt response after a fall is crucial for mitigating the physical and psychological effects (fear of falling (FoF) syndrome), which undermine the well-being of elderly individuals and their confidence in living independently and self-sufficiently [6].

Fall detection system (FDS), is proficient in discriminative falls from activities of daily living (ADL) thereby an alarm to remote monitoring point has been automatically produced immediately, and the user or patient under observation is suspected to have fallen [7]. The traditional machine learning (ML) approaches endure the shortage of labelled training databases and greatly depend on the extracted features by humans which creates it hard to utilize on massive platforms [8]. Deep learning (DL) has a new paradigm in the ML domain primarily determined by utilizing artificial neural networks (ANNs) and greater performance than the other standard ML approaches. The DL includes different networks namely recurrent neural network (RNN), restricted Boltzmann machines (RBMs), convolutional neural network (CNN), deep belief network (DBN), which have various features and abilities [9]. These networks can perform the learning process in unsupervised, semi-supervised, or supervised behaviors. Also, it advantages from the hierarchical layers targeted for finding appropriate higher-level features from the raw input data in place of utilizing manual features [10].

This article presents a new fall detection and classification using Jarratt-butterfly optimizer algorithm with deep learning (FDC-JBOADL) technique. The FDC-JBOADL technique applies median filtering (MF) approach to remove the noise. In addition, the FDC-JBOADL technique makes use of EfficientNet model for the extraction of relevant features from both motion patterns and appearance characteristics of individuals. Moreover, the classification of fall events occurs using long short-term memory (LSTM) network. Finally, the Jarratt-butterfly optimization algorithm (JBOA) can be employed for the optima hyperparameter choice of the LSTM model. A wide range of experiments was performed to validate the superior recognition results of the FDC-JBOADL technique.

2. RELATED WORKS

In recent years, the integration of innovative DL techniques and advanced sensor technologies has significantly enhanced the capabilities of classification and monitoring systems in various domains. For instance, Li *et al.* [11] introduced a novel DL framework that integrates temporal convolution networks (TCN) with gated recurrent units (GRU), aimed at extracting higher-level features for improved classification accuracy. Their research involved a comparative analysis against 2 extensively utilized ML classifiers and six existing DL approaches, leveraging 2 well-established open-source datasets collected from inertial sensors. Concurrently, Raeve *et al*. [12] proposed an innovative fault detection and alert system tailored for care centers, which utilizes bluetooth low energy (BLE) for wireless communication. This study also emphasizes the development of a real-time data filtering method to enhance the accuracy of measurements. Additionally, the exploration of millimeter-wave (mmWave) radar technology for unobtrusive human fall detection has been highlighted in [13]. This research involved collecting data from healthy young volunteers, with radar systems strategically positioned either on the side wall or overhead within a designated area. To address the underlying fault detection challenges, a CNN-based DL approach was also developed. Collectively, these studies underscore the transformative potential of integrating advanced DL methodologies with cutting-edge sensor technologies to improve monitoring and classification tasks across various applications.

This study also develops a CNN based approach to address underlying FD challenges. Building on these advancements, Yao *et al*. [14] proposed an efficient FD technique utilizing a joint motion map constructed from two parallel CNNs, innovatively employing the red, green, and blue (RGB) channels of pixels to capture relative motion data. Their method predicts the limits of stability and accurately identifies the initial and final key frames preceding a potential fall. Furthermore, the hybrid deep CNN model known as squeeze and excitation (SE)-Deep ConvNet, designed by Mekruksavanich *et al.* [15], enhances fall detection capabilities with the implementation of squeeze and excitation techniques. Collectively, these studies underscore the transformative potential of DL and advanced sensor technologies in improving FDS, ultimately contributing to enhanced safety and monitoring in various environments.

In recent years, the advancement of fault diagnosis techniques has gained significant attention in various fields, mostly in the context of high voltage direct current (HVDC) models and fall detection for the elderly. Jawad and Abid [16] proposed a novel approach for HVDC fault diagnosis that integrates a probabilistic generative algorithm based on feature selection (FS) and wavelet transform methods. Their methodology involves the extraction of noise from both non-fault and fault signals, followed by the application of ant colony optimization (ACO) to eliminate irrelevant attributes within the feature vectors. The refined features are subsequently utilized for training an ANN to effectively distinguish between non-fault and fault conditions. Concurrently, Lee *et al*. [17] introduced a dual verification strategy for fall detection in older adults, employing a combination of RGB cameras and inertial measurement unit-location (IMU-L) sensors. This approach is particularly innovative as it leverages wearable technology to monitor falls, with the IMU-L sensor providing real-time detection capabilities. To enhance the accuracy of fall classification, a DL method utilizing RNN is employed, marking a significant step forward in the consistency of FDS. This research highlights the intersection of advanced signal processing techniques and ML methodologies in addressing critical safety concerns in both electrical engineering and geriatric care.

3. THE PROPOSED MODEL

Falls represent a major health risk, particularly among the elderly population, leading to severe injuries and increased mortality rates. As such, the progress of automated systems for fall detection and classification has garnered considerable attention over recent years. This research introduces the FDC-JBOADL technique, a novel approach designed to develop the accuracy and effectiveness of fall event identification and classification through the integration of DL models. The FDC-JBOADL technique employs a multifaceted methodology that includes noise removal using a MF, feature extraction leveraging the EfficientNet architecture, fall detection using LSTM, and hyperparameter optimization through the JBOA algorithm. The workflow of the FDC-JBOADL method is exemplified in Figure 1, demonstrating the systematic process involved in recognizing and categorizing fall events. This innovative technique aims to assist the progress of automated FDS, advanced enhancement the safety and well-being of vulnerable populations.

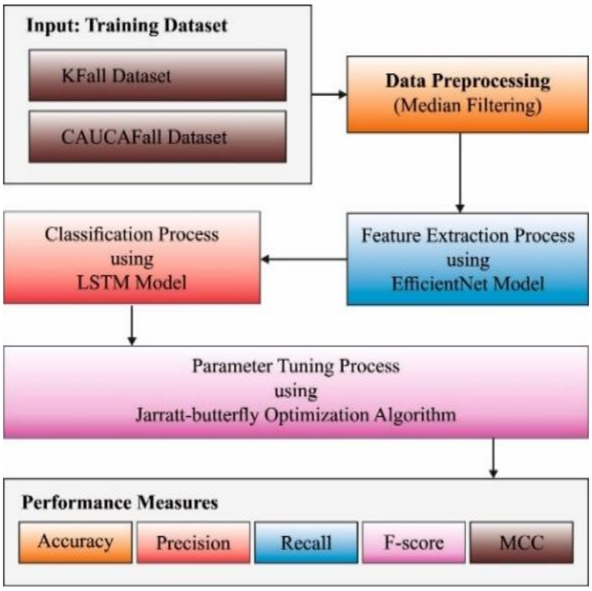

Figure 1. Workflow of FDC-JBOADL approach

3.1. Image pre-processing

To pre-process the input images, the MF technique is exploited in this study. It is a nonlinear digital image processing method used for preserving edges and reducing noise in images. It is very efficient at eliminating salt-and-pepper noises, where random white and black pixels appear throughout the image. The MF method includes substituting the value of all the pixels with median value of its neighboring pixels within the given kernel or window.

3.2. Feature extraction using EfficientNet model

For effectual identification of the feature vectors, the EfficientNet method can be employed. EfficientNet is a family of deep neural network (DNN) architecture that has been intended to accomplish remarkable performance while being computationally effective [18]. The basic concept behind EfficientNet is to simultaneously balance the model's depth, width, and resolution to attain best outcomes with less computational parameters and. Traditional model scaling techniques focus mainly on increasing the dimension (for example: width or depth), resulting in suboptimum performance. EfficientNet makes use of a compound coefficient to uniformly scale the 3D, which is derived from a series of experiments. The compound scaling coefficient is used for scaling the resolution, depth (number of layers), and width (number of channels) of the networks. The EfficientNet model has accomplished outstanding performances on computer vision task while being more effective than other DenseNet and ResNet architectures. They are widely applied for the tasks including object detection, image classification, and segmentation. There exist numerous variants of EfficientNet, namely EfficientNet-B0-B7, with various levels of performance and complexity. B0 is the simplest and smallest version, whereas B7 is the most complex and largest one. Based on the computational resource available and the task requirement, users can select the suitable variant.

3.3. Fall detection using long short-term memory

In this work, the LSTM framework can be utilized for the identification and classification of fall events. The LSTM network is an improved method of an RNN [19], [20]. Different CNNs namely multilayer perceptron (MLP) and RNNs could not be restricted to a unidirectional flow of data. It is loop done many layers and temporarily memorizes data which is employed later. In the meantime, an easy RNN is vulnerable to gradient disappearing problems, and the GRU and LSTM are established for solving the problem. The LSTM learns long-term dependencies, enduring appropriate to classify sequential data like credit card information. LSTM network comprises memory cell c_t, with input gate i_t, output gate o_t, and forget gate f_t. The 3 gates control that the data has been managed and employed. Figure 2 illustrates the structure of LSTM. The subsequent mathematical equations define the data flow in the LSTM layers as in (1) to (6).

$$i_t = \sigma(V_i x_t + W_i h_{t-1} + b_i) \tag{1}$$

$$f_t = \sigma\left(V_f x_t + W_f h_{(t-1)} + b_f\right) \tag{2}$$

$$\tilde{c}_t = tanh\left(V_c x_t + W_c h_{(t-1)} + b_c\right) \tag{3}$$

$$c_t = f_t \otimes c_{(t-1)} + i_t \otimes \tilde{c}_t \tag{4}$$

$$o_t = \sigma\left(V_o x_t + W_o h_{(t-1)} + b_o\right) \tag{5}$$

$$h_t = o_t \otimes tanh(c_t) \tag{6}$$

Whereas V_*, W_*, and b_* signifies the learnable parameter, h_* denotes the hidden layer, which, $*$ is employed in place of f, i, o, or c to signify the provided memory cell and gates. In the meantime, $\otimes$ denotes the element-by-element product; $tanh$ and σ denote the tanh activation and sigmoid functions.

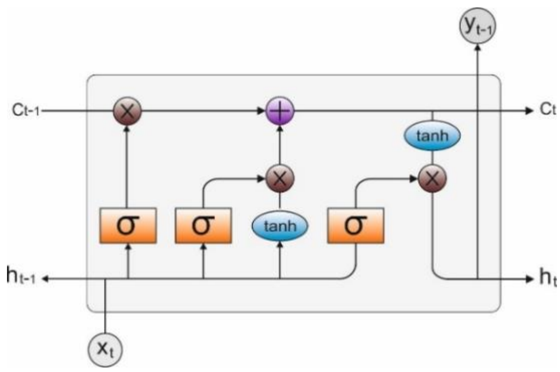

Figure 2. LSTM architecture

3.4. Parameter tuning using Jarratt-butterfly optimization algorithm

In recent years, the optimization of LSTM has garnered significant attention because of o their efficacy in handling sequential data. One of the promising strategies for enhancing the performance of LSTM networks is the integration of optimization algorithms, such as the butterfly optimization algorithm (BOA). While BOA has revealed that a powerful tool for various applications, it is not without its challenges, particularly with issues of divergence and the propensity to become trapped in local optima during the resolution of nonlinear systems of equations (NSE). To mitigate these limitations, the Jarratt's model is incorporated into the BOA framework, resulting in the development of the JBOA. This hybrid approach leverages the strengths of both algorithms, significantly improving the accuracy and convergence rate in solving NSE. Specifically, Jarratt's technique is employed iteratively within the BOA process, enhancing the candidate butterfly positions identified by BOA and ensuring that the most optimal solutions are selected based on fitness criteria. The integration of Jarratt's method not only accelerates the convergence process but also enhances the overall effectiveness of JBOA in resolving complex optimization problems. The following sections will detail the algorithmic framework of JBOA, illustrated through its pseudocode in Algorithm 1, and discuss its implications for parameter tuning in LSTM networks.

Algorithm 1. Pseudocode of JBOA

```
Objective function f(x), x = (x_1, x_2, ..., x_dim), dim = No. of dimensions
Create population initialization of n Butterflies x_i = (1,2,...,n)
Stimulus Intensity I_i at x_i is determined f(x_i)
Describe switching probability p, sensor modality c and power exponent a
While ending condition is not met do
   For all the butterflies bf in the population do
      Evaluate fragrance for bf
   End for
   Find the better bf
   for every butterfly bf in the population do
      Generate a modem r from [0,1]
      If r < p then
         Move toward solution or butterfly
      Else
         Move randomly
      End if
   End for
   Upgrade the value of a
end while
Compute Jarratt's location x_{n+1} using bf
Evaluate the fitness of x_{n+1} and x_bf
If Fitness (x_{n+1}) < Fitness(x_bf) then
   x_bf = x_{n+1}
End if
Output the better solution found (X_bf)
```

JBOA uses the modification given in the red box at the iteration end. Based on fitness value, this comparison was made between the BOA butterfly's location $\left(X_{bf}\right)$ and Jarratt's technique's location (X_{n+1}). At last, the best position that evaluates better fitness is chosen as an optimum solution.

The fitness choice is an important element in the JBOA classifier. Encoder performance can be executed for measuring the goodness of candidate outcomes. The accuracy value is the basic premise engaged for developing a fitness function (FF).

$$Fitness = \max(P) \tag{7}$$

$$P = \frac{TP}{TP+FP} \tag{8}$$

Where TP and FP represent the true positive ratio and the false positive ratio.

4. RESULTS AND DISCUSSION

This section evaluates the performance of the FDC-JBOADL methodology utilizing the KFall and CAUCAFall datasets. The KFall dataset [21], [22] includes various classes such as forward fall while attempting to sit down (20), backward fall while attempting to sit down (21), lateral fall while trying to sit down (22), forward fall while trying to get up (23), lateral fall while getting up (24), forward fall while sitting due to fainting (25), lateral fall while sitting due to fainting (26), Backward fall due to fainting (27), vertical (forward) fall while walking due to fainting (28), fall while walking with hands used to soften the impact due to fainting (29), forward fall while walking due to tripping (30), forward fall while jogging due to tripping (31), forward fall while walking due to slipping (32), lateral fall while walking due to slipping (33), and backward fall while walking due to slipping (34). Meanwhile, the CAUCAFall dataset [23] consists of 13,581 ADL labeled as "nofall" and 6,421 labeled as "fall". Sample images are illustrated in Figure 3.

Table 1 and Figure 4 demonstrates the overall classifier results of the FDC-JBOADL technique on the KFall dataset. The outcomes indicate that the FDC-JBOADL technique reaches effectual outcomes on both training set (TRS) and testing set (TSS). On the applied TRS, the FDC-JBOADL technique offers $accu_y$, $prec_n$, $reca_l$, F_{score}, and Matthews correlation coefficient (MCC) of 99.39, 99.39, 99.41, 99.30, and 99.03% respectively. At the same time, on the applied TSS, the FDC-JBOADL method provides $accu_y$, $prec_n$, $reca_l$, F_{score}, and MCC of 99.16, 99.32, 99.38, 99.25, and 99.01% correspondingly.

Figure 3. Sample images

Table 1. Classifier outcome of FDC-JBOADL algorithm on KFall dataset

Metrics	Training set (%)	Testing set (%)
Accuracy	99.39	99.16
Precision	99.39	99.32
Recall	99.41	99.38
F-score	99.30	99.25
MCC	99.03	99.01

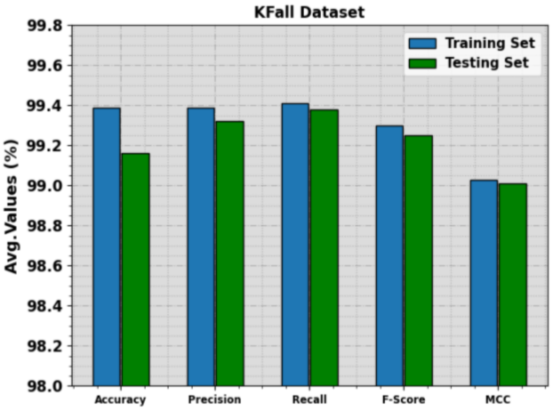

Figure 4. Classifier outcome of FDC-JBOADL approach on KFall database

The performance evaluation of ML methodologies is crucial for understanding their effectiveness in various applications. This study focuses on the FDC-JBOADL method, specifically its application to the KFall dataset, to analyze training and validation accuracies as well as loss metrics. As illustrated in Figure 5, the training accuracy (TR_accu_y) and validation accuracy (VL_accu_y) exhibit a positive correlation with the number of training epochs, indicating that increased epochs contribute to enhanced model efficacy on both the training and testing datasets. Furthermore, Figure 6 presents the trends in training loss (TR_loss) and validation loss (VR_loss) associated with the FDC-JBOADL approach. The results reveal a consistent decrease in both TR_loss and VR_loss as the epochs progress, underscoring the model's capability to minimize prediction discrepancies and improve classification precision. Collectively, these findings affirm the FDC-JBOADL method's potential in effectively identifying patterns and relationships within data, thereby establishing its significance in the realm of predictive analytics.

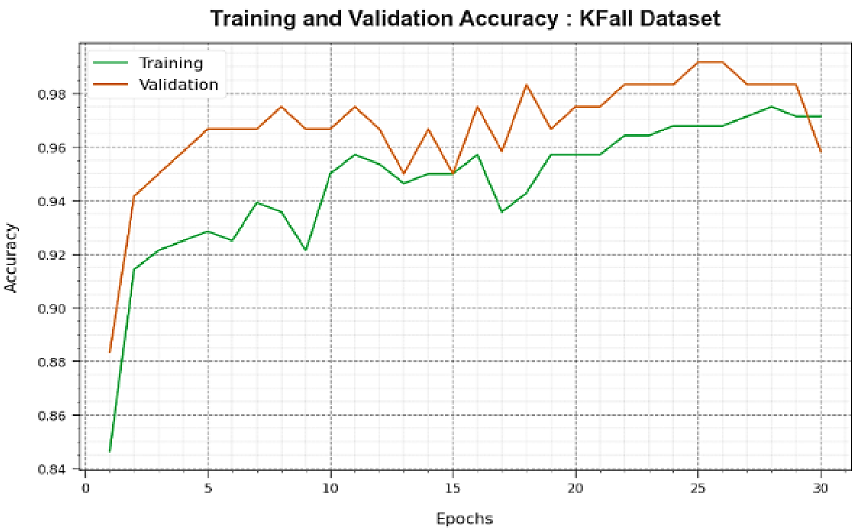

Figure 5. $Accu_y$ curve of FDC-JBOADL algorithm on KFall database

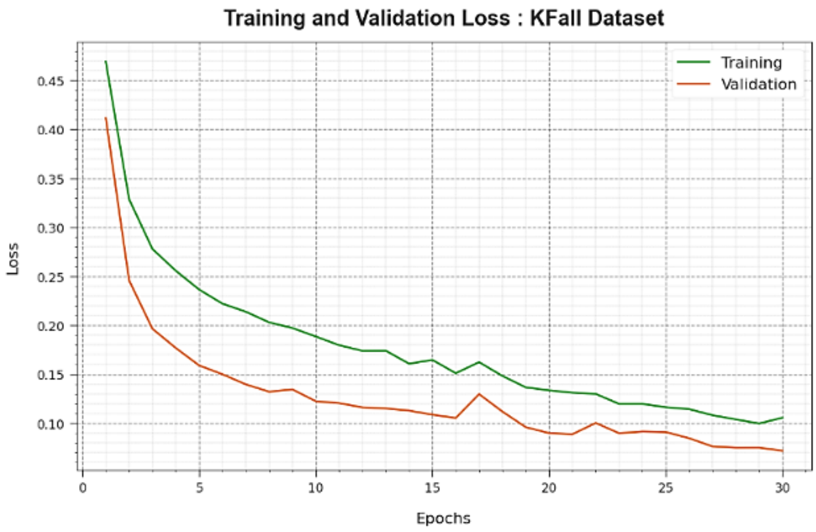

Figure 6. Loss curve of FDC-JBOADL algorithm on KFall dataset

Table 2 and Figure 7 signifies the classification outcomes of the FDC-JBOADL method on the CAUCAFall dataset. The outcomes specify that the FDC-JBOADL technique reaches effectual outcomes on both TRS and TSS. On the applied TRS, the FDC-JBOADL technique offers $accu_y$, $prec_n$, $reca_l$, F_{score}, and MCC of 98.81, 98.72, 98.54, 98.50, and 98.18% respectively. At the same time, on the applied TSS, the FDC-JBOADL technique offers $accu_y$, $prec_n$, $reca_l$, F_{score}, and MCC of 98.33, 98.27, 98.12, 98.20, and 98.04% respectively.

The evaluation of ML methodologies often hinges on their ability to accurately classify and predict outcomes based on training and validation datasets. In this context, the FDC-JBOADL method has been applied to the CAUCAFall dataset, revealing significant insights into its performance metrics. As illustrated in Figure 8, both TR_accu_y and VL_accu_y exhibits a positive correlation with the number of training epochs, suggesting that prolonged training enhances the model's efficacy on both the training (TR) and testing (TS) datasets. This trend underscores the importance of epoch duration in optimizing the efficiency of ML approaches. Moreover, Figure 9 presents the loss metrics associated with the FDC-JBOADL approach, specifically the TR_loss and VR_loss. These metrics provide a quantitative measure of the discrepancy among predicted outcomes and actual outcomes, with findings indicating a consistent decline in both TR_loss and VR_loss as epochs progress. This reduction in loss values further corroborates the model's increasing proficiency in identifying underlying patterns and relationships within the data. Collectively, these outcomes emphasize the solution of the FDC-JBOADL method in achieving precise classifications, thereby contributing to the broader discourse on the optimization of ML techniques in complex datasets.

The comparison study of the FDC-JBOADL technique in existing approaches take place in Table 3. The results indicate that the FDC-JBOADL method achieves enriched performance over other models [24], [25]. Based on $accu_y$, the FDC-JBOADL technique accomplishes higher $accu_y$ of 99.39% but the CNN classifier, LSTM algorithm, CNN-LSTM approach, and FDSNeXt models attain minimal $accu_y$ values of 85.69, 90.12, 84.04, and 91.87% respectively. In addition, based on $prec_n$, the FDC-JBOADL technique accomplishes higher $prec_n$ of 91.44% whereas the CNN classifier, LSTM algorithm, CNN-LSTM approach, and FDSNeXt algorithm attain lower $prec_n$ values of 91.28, 89.90, 91.07, and 99.39% respectively. Next to that, based on $reca_l$, the FDC-JBOADL method accomplishes higher $reca_l$ of 89.72% while the CNN classifier, LSTM algorithm, CNN-LSTM approach, and FDSNeXt system attain reduce $reca_l$ values of 90.67, 89, 90.05, and 99.41% correspondingly. At last, based on F_{score}, the FDC-JBOADL technique accomplishes higher F_{score} of 89.69% while the CNN classifier, LSTM algorithm, CNN-LSTM approach, and FDSNeXt methodology attain lesser F_{score} values of 91.39, 90.44, 90.75, and 99.30% correspondingly. These performances guaranteed the excellent solution of the FDC-JBOADL technique.

Table 2. Classifier outcome of FDC-JBOADL algorithm on CAUCAFall database

Metrics	Training set (%)	Testing set (%)
Accuracy	98.81	98.33
Precision	98.72	98.27
Recall	98.54	98.12
F-Score	98.50	98.20
MCC	98.18	98.04

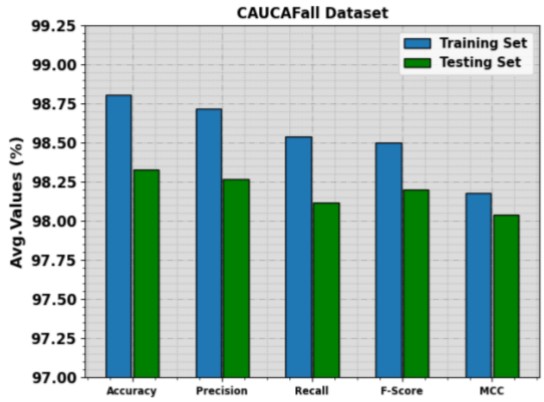

Figure 7. Classifier outcome of FDC-JBOADL algorithm on CAUCAFall dataset

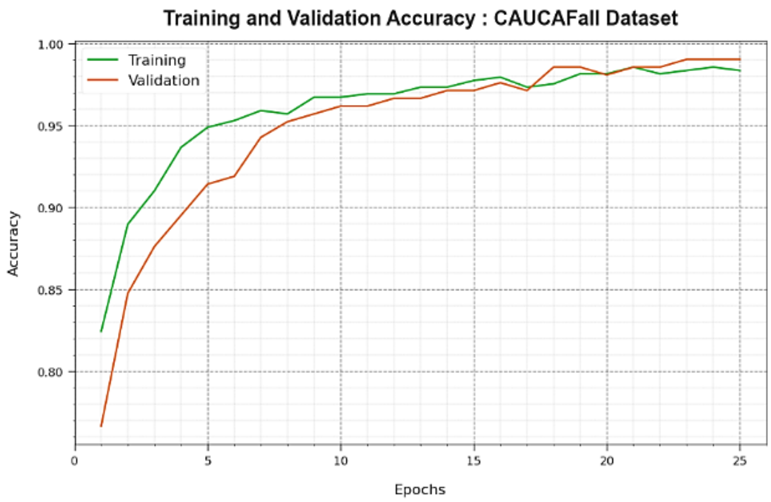

Figure 8. $Accu_y$ curve of FDC-JBOADL algorithm on CAUCAFall dataset

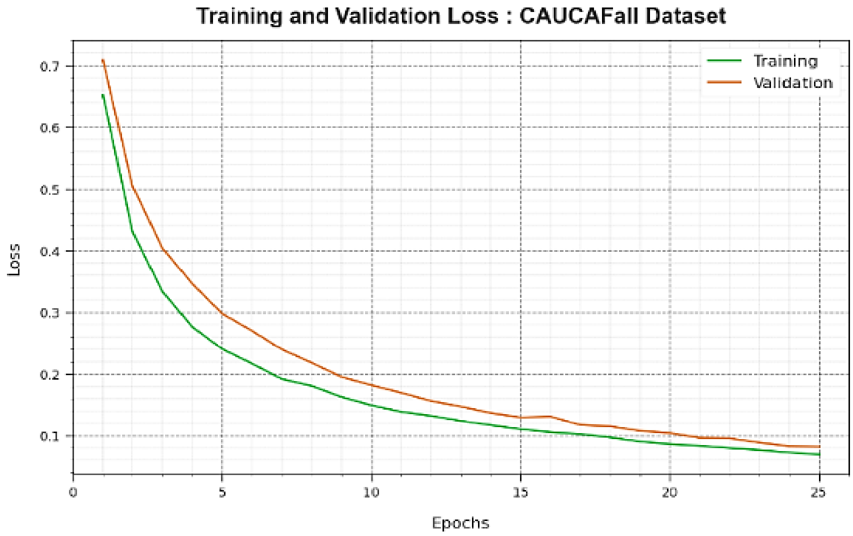

Figure 9. Loss curve of FDC-JBOADL algorithm on CAUCAFall dataset

Table 3. Comparative outcome of FDC-JBOADL algorithm with other methods

Model	$Accu_y$ (%)	$Prec_n$ (%)	$Reca_l$ (%)	F_{Score} (%)
CNN algorithm	85.69	91.44	89.72	89.69
LSTM algorithm	90.12	91.28	90.67	91.39
CNN-LSTM	84.04	89.90	89.00	90.44
FDSNeXt	91.87	91.07	90.05	90.75
FDC-JBOADL	99.39	99.39	99.41	99.30

5. CONCLUSION

This research highlights the efficacy of the FDC-JBOADL technique in automating the recognition and classification of fall events through the integration of advanced DL models. By employing a multifaceted approach that includes MF-based noise removal, EfficientNet for feature extraction, LSTM for fall detection, and JBOA for hyperparameter optimization, the FDC-JBOADL technique demonstrates significant improvements in recognizing and classifying fall incidents. The methodology not only leverages the strengths of EfficientNet in capturing both motion patterns and individual appearance characteristics but also ensures optimal performance through meticulous hyperparameter tuning. The comprehensive experimental validation underscores the excellent solution of the FDC-JBOADL technique compared to other systems, reinforcing its potential as a robust solution for fall detection in various applications. Future work concentrates on further refining the technique and exploring its applicability in real-time monitoring systems, ultimately contributing to enhanced safety and well-being for individuals at risk of falls.

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