Elderly standing imbalance detection using noise-resilient robust mean estimator and deep learning

Elderly Standing Imbalance Detection Using Noise-Resilient Robust Mean Estimator and Deep Learning

Drishya Raj[1], Shanfeng Hu[1], Nauman Aslam[1], Xiaomin Chen[1], Worasak Rueangsirarak[2], Surapong Uttama[2]
[1]Department of Computer and Information Sciences, Northumbria University, UK
[2]School of Information Technology, Mae Fah Luang University, Thailand
drsiblings@gmail.com,(shanfeng2.hu, nauman.aslam, xiaomin.chen)@northumbria.ac.uk, (worasak.rue, surapong)@mfu.ac.th

***Abstract*— Elderly standing imbalance is a critical public health concern, demanding robust and accurate detection techniques for improved safety and well-being. In this paper, we propose a novel method employing unsupervised learning and Denoising Autoencoder with Multi-Layer Perceptron networks, along with a custom adaptive Huber loss function and activation function, to classify standing states in elderly individuals. The existing Standing imbalance detection research includes difficulties such as addressing irregularities in pressure sensor data, largely stressing binary classification due to algorithmic efficiency considerations while dealing with heavy-tailed data. The approach utilizes open-source smart insole datasets, capturing left and right foot pressure data. The ensemble model DAE-MLP efficiently captures the temporal dynamics of the imbalance scores produced using the Noise-resilient robust mean estimator, enabling accurate and robust classification. This method adapts to varied degrees of data imbalance, resulting in more accurate learning. Through comprehensive evaluations, our method achieves an overall accuracy of 94% on a test dataset with 53 instances. This approach serves as a proactive standing imbalance detection system for the elderly, enhancing safety and quality of life by identifying and addressing standing imbalance risks. Our research introduces an innovative solution, paving the way for advancements in elderly healthcare and safety, reducing the risk of falls and related injuries.**

Keywords—Noise-Resilient(NR), Robust-Mean-Estimator(RME), Foot Pressure Data, Denoising Auto Encoder(DAE) -Multi-layer perceptron(MLP), adaptive Loss

I. INTRODUCTION

The degree of physical activity observed in elderly individuals plays a pivotal role in determining their general health and functional condition. As individuals age, their ability to maintain balance naturally declines, and this diminished balance is a factor contributing to major imbalances in the elderly population [5]. Imbalance-related issues and falls can result in severe injuries, such as fractures, leading to chronic pain, reduced quality of life, disability, or even mortality[10]. Statistics reveal that each year, over 50 percent of elderly individuals residing in care facilities and nursing homes, and 30 percent of those aged 65 and above living in the community, report experiencing falls [16][7].

The increasing number of physically inactive older adults places considerable pressure on healthcare services[3]. Standing balance impairment is a salient manifestation of various health conditions that engenders a discernible decline in functional ability [13]. The import of standing balance assessment traverses a broad spectrum, encompassing the prediction of minor imbalance disorders to the appraisal of surgical procedure risks [15].

Existing research on standing imbalance detection faces constraints, notably concerning detecting abnormalities and noise indices in data points by leveraging pressure sensors, and propensity for binary classification (Montanini et al., 2018; Quadros et al., 2018; Sadreazami et al., 2020; Maitre et al., 2021). These limitations are arguably linked to considerations related to the efficiency of classification algorithms (Jokanovic & Amin, 2018).This calls for a change in our approach, moving beyond conventional methods to more advanced ones [18]. Additionally, data from force device sensors is easily affected by unusual values and random noise, which is a concern. This requires new solutions to make the process of detecting balance problems more robust and dependable. Bridging these gaps is vital for pushing the field forward. It will help us create more effective models for identifying balance issues in older individuals, ultimately contributing to their safety, well-being, and overall quality of life. Therefore, In this study, we introduce a novel approach that combines unsupervised learning and NR-RME and DAE-MLP networks. Additionally, we employ a custom weighted Huber loss function and activation function to accurately classify standing states in elderly individuals.

The research team is in collaboration with Mae Fah Luang University Thailand to deploy it to an IOT force device with four force pressure sensors for testing the model's performance. The research is a part of the Digi Health Asia project, which is funded by the EU (https://digihealthasia.eu/)

To solve these challenges, this research introduces following contributions:

- The research utilizes an innovative unsupervised learning, NR-RME algorithm, and DAE-MLP networks model to classify standing imbalance in older people.The model incorporates a noise-resilient robust mean estimator with advanced features and diverse window sizes [2] which deals with the impact of heavy-tail noise and outliers in data.
- The efficacy and performance of the model are thoroughly examined and evaluated using a publicly available dataset obtained from a pair of sophisticated insoles that underwent preprocessing, normalization, PCA-based feature extraction, and a noise-resilient estimator to produce imbalance

scores, followed by analysis using a DAE-MLP network for accurate classification.

II. Related Work

Studying balance traits and analyzing the underlying trends in balance features can contribute to predicting and reducing the risks associated with imbalance [18]. By utilizing advanced technologies like motion capture, force plates, electromyography (EMG), sensors, and accelerometers, we can gather valuable data on kinematics and kinetic metrics, which offer valuable insights into a person's balance and postural control [17].

A force plate is a mechanical sensing system designed to measure the ground reaction forces and moments involved in human movements. These are commonly used in clinical settings by doctors and physio therapists to assess whether someone has good or poor balance. Machine Learning (ML) algorithms and statistical methods play a crucial role in analyzing motion and balance biomechanical characteristics to establish connections between various variables [18].

In an insightful study, Giovanini et al. categorized the balance traits of elderly individuals as either low or high fall risk and demonstrated the discriminative abilities of six different ML algorithms, along with 34 temporal/spatial characteristics extracted from the center of pressure data [4]. The Random Forest (RF) classification approach showed the highest accuracy at 64.9, and other classifiers like Naive Bayes (NB), Support Vector Machine (SVM), and K-Nearest Neighbours (K-NN) achieved performance with accuracy ranging from 75% to 77% [6].

Several studies have explored fall risk prediction using inertial sensors, such as accelerometers and gyroscopes. For instance, one study developed a statistical fall risk prediction system based on stability and symmetry of gait from accelerometer data [2]. Another research employed deep learning models to automatically derive features from raw accelerometer data for binary fall risk assessment [3]. Meanwhile, Hemmatpour et al. proposed a polynomial classification model using accelerometer and gyroscope data for real-time fall prediction, achieving 99.2 accuracy [9]. Bizovska et al. used inertial sensors and a clinical score to assess local dynamic stability during gait, reporting an AUC of 0.75 for fall risk assessment [10].

However, these studies faced challenges with sensor placement affecting model performance and preprocessing time required for data filtering and were not particularly focused on standing balance. In another notable study, Hoffman et al. employed a recurrent neural network (RNN) based on long short-term memory (LSTM) to examine the walking patterns of 42 individuals using a capacitive sensor floor [19]. Their findings indicated the potential of combining neural networks with sensor-based data for medical research. Additionally, Savadkoohi et al. found that a neural network model consisting of one layer of 1D CNN, one layer of LSTM, and a Dense layer was highly effective in predicting human balance impairment using pressure-plate time series signals [18]. The One-OneOne Neural Networks classification model showed improvement in performance, achieving precision, recall, and accuracy of 100, 100, and 99.9, percent respectively.

Gait anomaly detection has seen advancements through the development of automated techniques utilizing Convolutional Neural Networks. Researchers have explored the effectiveness of pre-trained CNN models like Vgg16, ResNet50, MobileNetV2, and DenseNet in detecting gait anomalies, achieving higher accuracy and reduced computation time when compared to comparable research fields[17]. Notably, these CNN-based approaches analyze sensor images, offering a simpler alternative to video-based methods, eliminating the complexities of 3D data preprocessing.

Gait disorders pose substantial challenges to individuals, leading to a loss of autonomy, increased risk of falls and injuries, and reduced quality of life. Timely and accurate gait disorder detection is essential for improving patient mobility, preventing falls, and identifying underlying causes. Traditional manual methods, performed by medical specialists, have proven rigid and time-consuming. Thus, this literature review highlights the significance of developing a streamlined GAD approach based on CNN models, particularly transfer learning, to classify foot anomalies effectively. The promising results of these models, such as the Vgg16 achieving 97.15 accuracy in distinguishing normal and abnormal gait, demonstrate the suitability and potential of the proposed technique but limited to gait disorders.

Therefore, In this study, we introduce a novel approach that combines unsupervised learning With the NR-RME algorithm and DAE-MLP ensemble model. Additionally, we employ an adaptive Huber loss function to accurately classify standing states in elderly individuals.

III. Methodology

In this study, a publicly available dataset from advanced insoles was used to capture detailed foot dynamics, including pressure distribution and movement. Data preprocessing involved segmentation, filtering, and standardization using Z-scores. Principal Component Analysis (PCA) was used for feature extraction. An innovative noise-resilient robust mean estimator, inspired by the Sample Median algorithm, was applied to compute imbalance scores. Finally, a DAE-MLP network was used to analyze temporal dynamics for accurate classification.

A. Data Acquisition

The dataset employed for standing imbalance detection is the Smart OpenGo Insole [1] comprising 10 healthy subjects with an average age ranging from 25 to 35 years. The mean height for males lies within the range of 174 to 179 cm, while for females, it varies from 160 to 163 cm. The average weight for males spans from 70 to 75 kg, and for females, it ranges from 52 to 60 kg. Although the dataset primarily focuses on fall detection, the present study solely observes the standing pressures of each subject, dismissing other data points as irrelevant. Each standing pressure file in the dataset encompasses 39 columns, incorporating 13 pressure sensors for both the left and right foot, in addition to accelerometer values for both feet. For the current analysis, only the indispensable foot pressures are taken into account, utilizing specific pressure sensor points identified as pivotal for detecting standing imbalance.

B. Data Preprocessing and Feature Extraction

Filtering : The data preprocessing approach, inspired by Lin et al. (2022), begins with filtering the sensed raw data to reduce noise interference. A Butterworth low-pass filter is applied, setting the cutoff frequency at 5 Hz, as per the findings of Price (2018)[14], aligning with the human standing frequency range. This filtering step ensures that the subsequent analysis focuses on clean and reliable data, consistent with the methodology employed in Lin et al.'s research. It is depicted in figure 1.

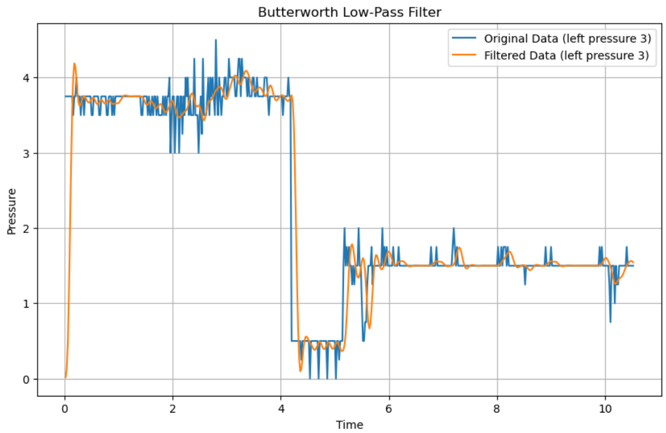

Figure 1: Left foot pressure filtered data

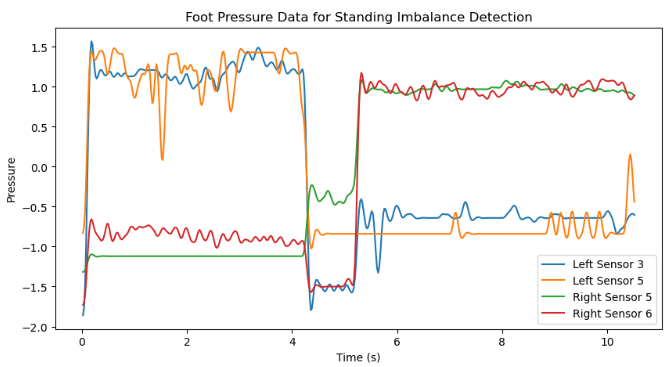

Figure 2: Raw Pressure data variations

Z-Score Standardization: Inspired by Lin et al. (2022), Z-score standardization is introduced to address biases arising from individual weights, which could ly impact network training. Following Lin et al.'s approach, Z-score standardization is performed individually for each collected pressure data, using the formula Zp = (zp-μ)/ σ. The mean () and standard deviation () of the sequence Zp are computed accordingly. With N set to 29, encompassing data from 13 pressure sensors in each foot.

Feature Extraction: In our paper, we applied a feature selection technique using Principal Component Analysis (PCA) and K-means clustering to identify the most important features from the sensor data. We selected 38 principal components to represent the data, capturing most of the variance in the original feature space.We utilized PCA to identify the most important sensors from the sensor data. The component loadings represent the contribution of each sensor to the principal components, and the scree plot shows the proportion of variance explained by each principal component as shown in figure 2.

To assess the importance of each sensor, we calculated the absolute weights for each sensor in each component by taking the absolute values of the loadings. Then, we summed the absolute weights for each sensor across all components to get an overall measure of sensor importance. The results provide valuable insights into the contribution of individual sensors to the overall variance in the data and will be crucial for our standing imbalance detection analysis, as we could focus on the most relevant sensors for accurate and efficient detection. The

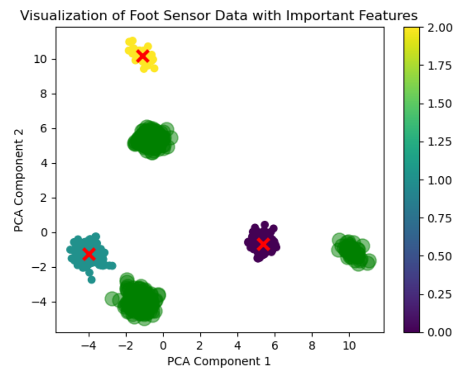

Figure 3: PCA Performance

outcomes of this feature selection process were instrumental in subsequent analyses and models, as it revealed the crucial aspects of the sensor data that have the most impact on standing imbalance detection.

C. Noise resilient Robust Mean Estimator (NR-RME)

In the context of univariate analysis, the presented estimator, Algorithm, simply calculates the sample median based on the observed data[2]. While this approach may seem simple, it exploits the essential relationship between the mean and median in symmetric distributions. However, this apparent simplicity has consequences concerning the impact of contamination in the Huber contamination model. In the subsequent section, it has been provided the theoretical bound achieved by this estimator,

$$\frac{\epsilon}{2(1-\epsilon)} + \frac{1}{1-\epsilon}\sqrt{\log(2/\delta)/n} \le t. \quad (1)$$

as demonstrated in the comprehensive study conducted by Altschuler et al. (2018).

This process relies on a sliding window technique, which permits a granular examination of the data's temporal characteristics. By computing the absolute differences between the second-order differences of the two time series datasets, we effectively capture the nuanced variations and disparities present within the data. Within each sliding window, the median score is ascertained using the sample median function, with the window size. For each specific window size, we compare the associated imbalance score with a predetermined threshold value. Should the imbalance score surpass the established threshold, it is promptly assigned a class label of 1, thereby signifying an imbalanced state. Conversely, if the score falls below or equals the threshold($p<0.05$)[20], it is firmly labelled as 0, which denotes a balanced state. This deliberate classification procedure results in an array of class labels, effectively capturing the classified imbalance scores. To facilitate a thorough and insightful analysis, we subsequently consolidate the imbalance scores and their corresponding class labels into a well-organized and structured data frame. This data frame presents a comprehensive view of the imbalance scores across various window sizes, offering a profound understanding of the temporal patterns associated with balanced and imbalanced states in the time series data.

D. Ensemble Model DAE-MLP

Traditional autoencoders, especially when equipped with deep architectures, are prone to being adversely affected by noise. In cases where the training data lacks clarity or is corrupted, the encoder output tends to exhibit less sparsity in the distribution of node weights. Consequently, the risk of overfitting becomes more pronounced, leading the model to memorize the training data rather than learning meaningful patterns. To tackle this challenge and enhance the model's robustness, a novel approach is employed, involving the introduction of random noise into the encoder input. This process randomly corrupts one of the input features **using** a stochastic term. By adopting this innovative strategy, the model gains the ability to effectively navigate through data imperfections and maintain its performance[1]. A Dropout layer with a rate of 0.5 is included in this architectural hierarchy. This layer was constructed by randomly removing 50% of the neurons from the previous layer in order to prevent overfitting and increase generalization and robustness.

Multi-Layer Perceptron (MLP) The Multi-Layer Perceptron (MLP) is a variant of the deep learning neural network family. It consists of an input layer, two or more hidden layers, and an output layer. Each layer contains multiple interconnected neurons, and the connections between neurons have associated weights. The neurons in the hidden layers use activation functions to introduce nonlinearity into the network.

Mathematically, the output of a neuron k in the MLP can be represented as follows:

$$y\_k = f(u\_k + b\_k) \quad (2)$$
$$u\_k = \sum(w\_\{ki\} * x\_i) \quad (3)$$

Where x_1, x_2, x_3, ..., x_n denote the input signals, w_{k1}, w_{k2}, w_{k3}, ..., w_{kn}.

MLP are trained using the backpropagation (BP) algorithm, which follows an error-correction rule. During training, the network processes input data and computes outputs. The error is then calculated by comparing the target values with the network's outputs. The weights and biases are adjusted using optimization techniques to minimize the error. The training process iterates until the network reaches a predefined minimum allowable error, often measured using mean square error (MSE) as the error function. The architecture of MLP-NNs allows them to handle complex tasks and learn intricate patterns from the data. By adjusting the number of hidden layers and neurons in each layer, MLPs can adapt to various problem complexities.

E. Integration of NR-RME and DAE-MLP

In the initial stages of data preprocessing, time series data, which includes pressure data from both the left and right foot, undergoes essential transformations to ensure numerical consistency. By converting the data to float type, we facilitate further computations and analyses. Next, we employ a robust statistical method called the Noise-Resilient Robust Mean Estimator (NR-RME) to calculate the imbalance scores. This technique efficiently handles noisy data and outliers, making it well-suited for our analysis. Using a sliding window approach, we compute the absolute differences between the second-order differences of the two time series datasets. This process captures the variations and disparities present in the data, even in the presence of noise.

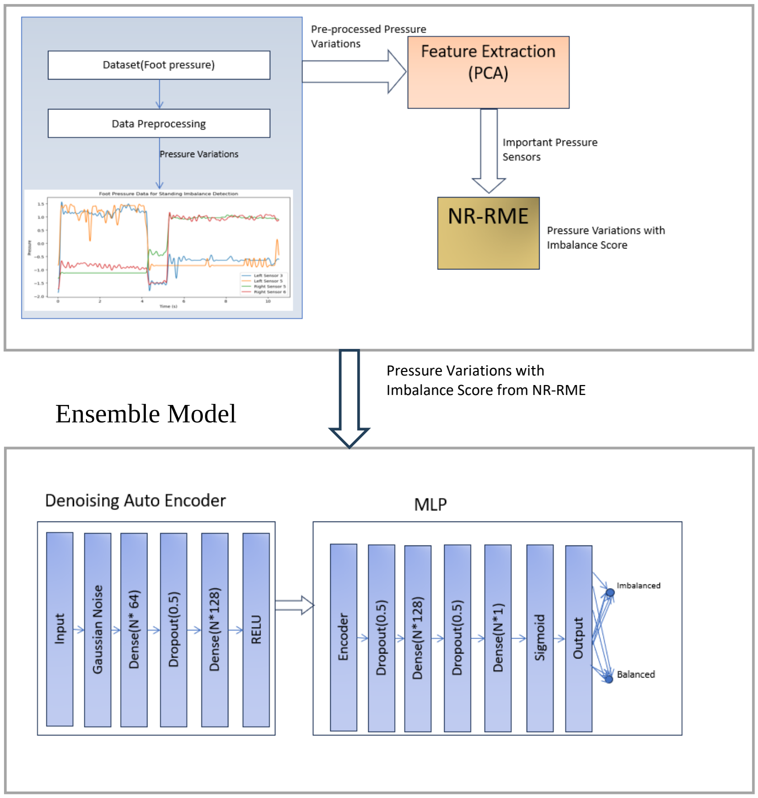

Figure 4: Model Architecture

Within each sliding window, we apply the NR-RME to estimate the median score. The window size for the NR-RME computation is determined by the parameter ”windowsizes.” These calculated imbalance scores are subsequently saved, as they will be crucial for the data labeling phase. Since our dataset is unsupervised, the imbalance scores play a pivotal role in attributing class labels to each data point. By thresholding the scores, we classify the data into balanced and imbalanced states. The adaptive Huber loss function is a specialized technique introduced to enhance the performance and robustness of regression models. It is a combination of the squared loss (Mean Squared Error, MSE) and the linear loss (Huber loss). The adaptive Huber loss calculates the residual, which measures the difference between the predicted value and the true target value.

A threshold parameter called ‘δ ‘ is computed based on the average magnitude of the residuals. The loss function operates in the following manner: If the absolute value of the residual is smaller than ‘δ ‘, it applies the squared loss (0.5 times the square of the residual). This encourages smooth and stable predictions when the model’s predictions are close to the true values. However, when the absolute value of the residual exceeds ‘δ ‘, the function switches to the linear loss, which penalizes large residuals proportionally. This linear component reduces the impact of outliers and promotes model stability. By summing up the individual losses for all predictions, the adaptive Huber loss provides an overall measure of the model’s performance. Its adaptability based on the magnitude of residuals allows it to effectively handle noisy and diverse datasets, making it a valuable tool for training models.

$$L(y_t, y_p) = \frac{1}{N} \sum_{i=1}^{N} \begin{cases} \frac{1}{2} \cdot \left(y_t^{(i)} - y_p^{(i)}\right)^2, \ if \ |y_t^{(i)} - y_p^{(i)}| < \delta \\ \delta \cdot |y_t^{(i)} - y_p^{(i)}| - \frac{1}{2} \cdot \delta^2 \ , \ otherwise \end{cases} \quad (4)$$

y_t: representing the true labels of the samples,
y_p, which denotes the predicted labels by the model,
δ, difference between the true and predicted labels .

The noise injection serves to augment the Denoising Autoencoder’s (DAE) resilience and finesse in extracting pertinent information from the corrupted input, elevating its adaptability to hitherto unseen data. Subsequently, the DAE incorporates two dense layers, each encompassing 64 and 128 neurons, respectively, and distinguished by the transformative prowess of the Rectified Linear Unit (ReLU) activation function. Effectively operating as masterful information processors, these layers skillfully detect intricate relationships within the data. Furthermore, a Dropout layer intervenes post the first dense layer, imparting an essential regularizing influence by randomly deactivating neurons during training. This prudent measure curtails the risk of overfitting. To optimize the DAE’s denoising potential, the ensemble model employs the adaptive Huber loss function. During the model training process, the DAE conscientiously learns to artfully reconstruct denoised data from the corrupted input, exhibiting a refined acumen in representing the data gleaned through the learned encoder part. Intriguingly, the extracted encoder part is ingeniously harnessed as a formidable feature extractor for the subsequent MLP, the neural epicenter for classification endeavors.

Augmented with Dropout layers, the MLP deftly interfaces with the learned features to further refine the classification process. Equipped with two dense layers of 128 neurons, the MLP deftly distills the essence of the extracted features into precise classification outputs. The denouement manifests in a final dense layer with a sigmoid activation, skillfully generating probabilities indicative of input belonging to a designated class. The model is honed during training, where its mettle is evaluated against a substantial 50-epoch duration, efficiently assimilating knowledge and experience for discerning performance. In essence, this ensemble architecture stands to obtain an classification efficiency and its proven efficacy through training and validation.

IV. Comparative Analysis

In this study, we designed a series of experiments using Keras and TensorFlow 2.11.0 to analyze and compare different configurations. Python 3.9.13 environment was utilised for our research. To ensure accurate results, we carried out the training and testing processes with great precision on a high-performance computer running Windows 11. This computer was powered by a powerful 2.42 GHz Intel Core 11th Gen i5-1135G7 CPU, a choice that played a critical role in maintaining the reliability of our study's findings.

The dataset consisted of 525 rows and 7 columns, including time, pressure readings, imbalance scores, and class labels. Time represented session duration, while pressure readings came from left and right positions. Imbalance ratings were precomputed to enrich the dataset. For binary classification, we developed an ensemble model. It combined Denoising Autoencoder (DAE) and Multi-Layer Perceptron (MLP) classifiers to benefit from DAE's noise reduction and feature extraction abilities, along with MLP's classification capability. The DAE had two key components: a Gaussian Noise layer introducing controlled noise and a Dense layer with 64 units responsible for extracting meaningful patterns from the noisy input data.

This architectural hierarchy includes a Dropout layer with a 0.5 rate. By randomly deactivating half of the neurons from the preceding layer, this layer was created to prevent overfitting and to promote generalization and robustness. Another Dense layer with 128 units that served as the basis for the next MLP classifier was added to the ensemble model at the end. Due to its complex design, the model was able to forecast events based on the useful attributes that the DAE had collected. The MLP classifier showed a two-tiered structure as we moved ahead. A Dropout layer with a 0.5 rate was achieved by the initial Dense layer, which had 128 units. The goal of this design was to prevent overfitting and retain the model's dependability. A single-unit Dense layer served as the output layer.

Throughout the DAE's training, we observed its steady improvement over 50 rounds. With the use of Adaptive Huber Loss, the training loss was decreased from 0.1410 to just 0.0053. After training the DAE, we proceeded to train the MLP using the encoder data. The MLP improved over time, starting with an accuracy of about 65.48%. The model accuracy improved as well, reaching around 96.23% indicating accurate classification of standing imbalance.

The classification report encompasses a variety of important metrics such as precision, recall, F1-score, support, accuracy, macro average, and weighted average. For class 0, the model achieved an impressive precision score of 0.96. This means that 96% of instances predicted as class 0 were correctly assigned. Furthermore, the recall score of 0.92 indicates that the model accurately identified 92% of the true class 0 instances.

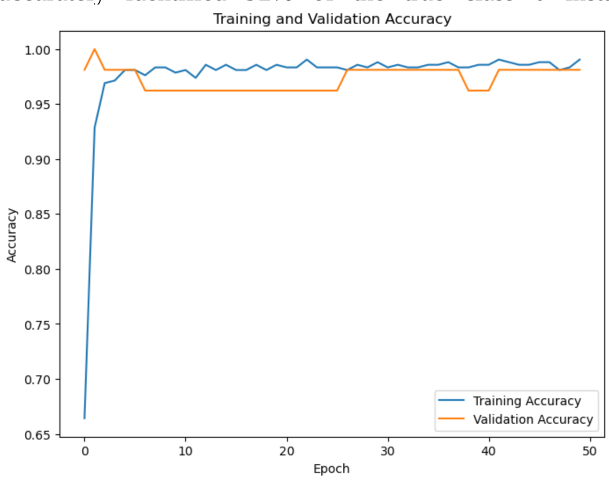

Figure 5: DAE-MLP Training and validation Accuracy

In Figure 5, we observe that the F1-score, standing at 0.94, reflects a harmonious combination of precision and recall, underscoring the model's ability to accurately classify both positive and negative instances of class 0. When considering class 1, the model exhibits a precision value of 0.93, denoting that 93% of instances classified as class 1 truly belong to the positive category. Simultaneously, the recall score of 0.97 indicates that the model effectively recognized 97% of the true class 1 instances. The F1-score for class 1, at 0.95, highlights a well-balanced relationship between precision and recall, contributing to a refined performance. Altogether, the model

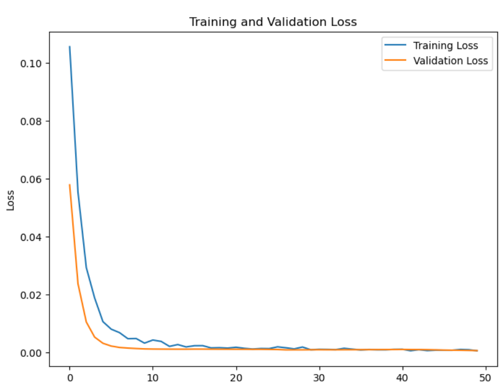

Figure 6: DA-MLP Training and Validation Loss

achieves an overall accuracy of 0.94, signifying the correct classification of 94% of all instances.

As Shown in Figure 6, the macro average, which takes an even-handed approach to precision, recall, and F1-score across all classes, achieves a value of 0.94. This underscores a balanced performance in the binary classification task. Likewise, the weighted average, which considers class imbalances, also reaches 0.94, succinctly encapsulating the model's performance across both classes. These findings reinforce the effectiveness of our ensemble model, where the fusion of denoising and classification methods synergistically aligns. This holds great promise for real-world applications requiring accurate binary classification.

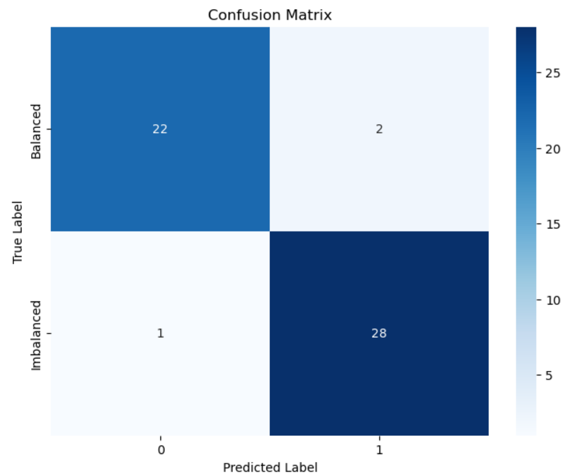

Figure 7: Confusion Matrix

The Confusion Matrix is depicted in Figure 7, providing insight into the model's performance. Additionally, we calculated the Area Under the Receiver Operating Characteristic Curve (AUC-ROC) for our binary classification model to be 0.9167. This crucial metric assesses the model's ability to distinguish between positive and negative instances. An AUC-ROC value of 0.9167 indicates strong discrimination, as the model achieves a high true positive rate while minimizing false positives. The AUC-ROC value ranges from 0 to 1, with 0 indicating poor performance and 1 indicating perfect classification. Therefore, a value of 0.9167 signifies that our model outperforms random guessing and excels in binary classification tasks.

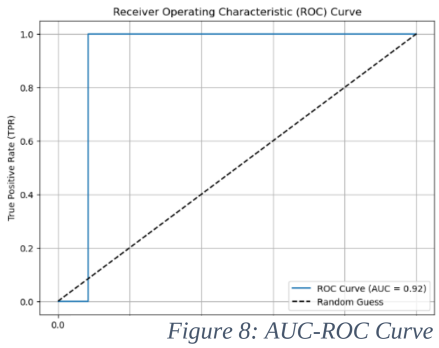

Figure 8: AUC-ROC Curve

Table 1:Performance Evaluation

Model	Classification Report			
	Accuracy	***F1 Score***	***Precision***	***Recall***
DAE-MLP With NR-RME	94%	94	96	*92*

V. Conclusion

In our study, we have introduced an innovative approach that focuses on detecting balance issues within the elderly population during instances of standing posture. This matter holds great significance due to the increased vulnerability to falls and related injuries faced by this demographic. Our method comprises a combination of two distinct methodologies: the Noise-Resilient Robust Mean Estimator (NRRME) and a composite model involving a Denoising Autoencoder (DAE) in conjunction with a Multi-Layer Perceptron (MLP).

The NRRME algorithm plays a pivotal role by computing mean values from data procured through wearable devices. This computation remains reliable even when the dataset is subject to disruptive influences, intrinsic noise, or heavy-tailed data points. This robust adaptability is essential for real-world scenarios, wherein data integrity can be susceptible to various factors. The combined DAE-MLP model then makes use of these improved data representations, improving feature extraction and ultimately the classification process's precision.

Our study was based on data gathered from foot pressure sensors attached to elderly participants during various standing activities. The dataset had been preprocessed, which included the removal of unwanted noise and abnormalities. Here, NR-RME algorithm contributed a vital part in maintaining the correctness of mean value predictions, providing as a basis for accurate statistical computations. Our model's DAE component proved essential in revealing key dataset patterns, which provided the MLP with a solid basis for the binary classification task—specifically, recognizing instances of balance irregularities. The results obtained confirm the effectiveness of our approach. The NR-RME with DAE-MLP algorithm had a commendable 94% accuracy rate in recognizing instances of standing imbalance, demonstrating its resilience in the face of data complexities and inconsistencies.

Nevertheless, it is important to acknowledge the limitations of our approach. The most important of them is the requirement for labeled data, which is required for both model training and evaluation. The human-annotated data collection procedure adds subjectivity and potential inaccuracies, which we constantly acknowledge. Furthermore, the universal applicability of our technique across multiple situations and demographic strata necessitates a thorough evaluation to assure robustness and reliability.

The development of strategies aimed at reducing reliance on annotated data, potentially through the introduction of semi-supervised learning paradigms, opens up exciting prospects for broadening the scope of our approach. The incorporation of real-time monitoring capabilities into wearable devices and sensor arrays opens the door to the possibility of continuous monitoring and rapid intervention. The use of contextual information, including environmental variables, has the potential to improve accuracy and adaptability. In conclusion, our research lays a solid foundation for furthering standing imbalance issues prevention measures and improving senior healthcare. This undertaking, on the other hand, is conscious of the need for continual refinement and investigation of its varied possibilities.

VI. Acknowledgement

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