Applied Computer Systems
ISSN 2255-8691 (online)
ISSN 2255-8683 (print)
June 2024, vol. 29, no. 1, pp. 45–52
https://doi.org/10.2478/acss-2024-0006
https://content.sciendo.com

Determination of Ataxia with EfficientNet Models in Person with Early MS using Plantar Pressure Distribution Signals

Taner Tuncer[1*], Aslı Sesli[2], Seda Arslan Tuncer[3]
[1–3]*Firat University, Elâzığ, Turkey*

Abstract **– Multiple Sclerosis (MS) is a central nervous system disease that causes ataxia and balance disorders. In ataxia, the first symptom is usually seen as gait disturbance. In gait ataxia, symptoms can be clinically defined by shortened stride length and irregular strides. Evaluation of gait disturbance in clinical cases is important for the detection of the first stage of ataxia. With the increasing amount of data, high-performance models can be produced, especially in the field of healthcare, with computer machine learning, deep learning and artificial intelligence methods. This study aimed to identify ataxia in individuals with Multiple Sclerosis (MS) by analysing images that encompass plantar pressure distribution signals. A total of 105 images, each containing plantar pressure distribution signals, were utilized to extract features through pre-trained EfficientNet architectures. Then the feature vectors obtained were classified by SVM, k-NN, and ANN methods. As a result of this study, the best classification performance was obtained with SVM classifier with 88.09 % Acc, 80.55 % Sen, 93.75 % Spe and 85.29 % F1 Score. The results show that the study will help the clinician in the detection of PwMS ataxia and will be a pioneer for future studies.**

Keywords **– Deep learning, feature extraction, image classification.**

I. Introduction

Multiple Sclerosis (MS) is a chronic, inflammatory, and autoimmune disease of the central nervous system, causing a variety of signs and symptoms in which multiple demyelinating plaques spread across time and space [1]. Ataxia, occurring due to cerebellar, vestibular, and/or sensory system problems, is one of the most challenging symptoms of MS. MS is associated with muscle strength loss, spasticity, sensory problems, and fatigue-related gait disorders. The severity and characteristics of ataxic symptoms vary depending on the presence of these issues, which typically occur simultaneously [2]–[4]. Increasing awareness of the importance of walking to quality of life and functional independence has prompted many research groups to examine the pathophysiology, epidemiology, and clinical and therapeutic aspects of these motor functions [5], [6]. In PwMS, gait changes are difficult to detect and understand. Some studies report speed, cadence and stride length, and increased duration of double support, while others fail to detect any differences in healthy individuals or find them in a few parameters [7]–[9].

The human eye can perceive 18–25 images per second. For this reason, objective evaluation of movements that occur within milliseconds during walking is a difficult process. It is clinically difficult for physicians to diagnose minimally interactive gait differences, especially in the early stages of the disease, in individuals who are not yet symptomatic, or whose EDSS score is below two. Wearable technology or Win-Track platforms are used to obtain data from patients with current methods [10]. Nevertheless, the data acquired for diagnostic purposes undergoes direct evaluation by specialised physicians. High-performance decision support systems will be very important in terms of early diagnosis of the disease and helping physician evaluation in this area. Therefore, machine learning or deep learning methods have been used in the literature to detect MS or ataxia in different diseases other than MS [11]–[15]. On the other hand, machine learning-based approaches using gait pressure distribution signal images for ataxia detection in PwMS have not been used in the literature. Therefore, the present study is a pioneer in the field.

In this study, it is aimed to detect ataxia for PwMS with a deep learning-based approach using an image dataset containing plantar pressure distribution signals. In the study, an alternative, objective and low-cost method is proposed to help physicians diagnose PwMS in the early stages.

Current techniques for diagnosing MS can be broadly divided into two types: sensor-based and image-based. Sensor-based techniques involve installing a sensor and analysing its signals. Using wireless inertial sensors mounted around the ankle joint, LeMoyne et al. used a machine learning approach to wirelessly transmit the accelerometer and gyroscope signal recordings to a cloud computing source for post-processing and then differentiate between sick and healthy gait individuals [11]. Kaur et al. used multiple machine learning approaches and compared them after acquiring gait data during self-walking on an instrumented treadmill for MS prediction [16]. Meyer et al. evaluated the performance of traditional machine learning models to measure fall risk in individuals with PwMS, using a

* Corresponding author’s e-mail: ttuncer@firat.edu.tr
Article received 2024-02-16; accepted 2024-07-12

feature set manually calculated from wearable accelerometer data, extracted from spatio-temporal gait parameters, patient-reported measurements, and clinical evaluations. As a result, they found that the BiLSTM deep learning model provided the highest performance with 0.88 AUC [17]. Hu et al. applied machine learning techniques to raw walking path data to distinguish MS patients from healthy controls. To improve machine learning model performance, they added some new features (finger direction, trunk area, base of support area, foot length, foot width, and foot area) in addition to standard parameters and increased the performance rate [18]. Alaqtash et al. developed an automatic gait classification tool. Classification of gait patterns of healthy, cerebral palsy and MS subjects using three components of GRF data (FX, FY, and FZ) and different machine learning algorithms, using two feature extraction algorithms and two classifiers were developed in [19].

Image-based techniques generally involve studies on magnetic resonance images (MRI). For example, Jannat et al. detected MS lesions from MRI scans with a 98.24 % success rate using VGG16, one of the transfer learning methods of Convolutional Neural Network (CNN), to automatically detect and classify MS disease [20]. Shrwan et al. obtained 99.2 % classification accuracy for Multiple Sclerosis brain lesion classification from MRI Images and 99.7 % classification accuracy for Pituitary Tumour classification with the help of the CNN for the classification of brain-related diseases [21]. Ekşi et al. proposed a computer-aided detection system for the automatic detection of MS lesions from MR images. The proposed system performs lesion segmentation using Fuzzy-C Means (FCM) and morphological operations. In the study, lesions detected by an expert on MR images and lesions detected by the proposed system were compared according to the Jaccard similarity criterion [22]. Kaya et al. employed pre-trained deep learning models, including VGG16, ResNet, MobileNet, VGG19, DenseNet, and NasNetMobile, to analyse static bipedal pressure distribution image data. The authors conducted feature extraction as part of their methodology. Extracted features were classified with SVM, k-NN, ANN, and the VGG19-SVM hybrid model obtained an accuracy value of 95.12 % [23]. Sesli et al. used the images containing plantar pressure distribution signal images to classify with the help of pre-trained hybrid CNN networks and obtained an accuracy value of 85.71 % with the VGG19-SVM model [24].

A. Motivation

Nowadays, the need for new and effective methods in the diagnosis and follow-up of complex neurological diseases such as MS is increasing. In this context, early detection and management of symptoms such as ataxia can significantly impact patients' quality of life. The main motivation of this study is to provide an alternative approach to traditional methods to detect ataxia symptoms in MS patients.

Going beyond traditional medical imaging techniques, this study aims to develop a high-performance model for ataxia detection using baseline pressure distribution signals. Clinically evaluating the early stages of gait ataxia, especially irregularities in gait patterns and shortness of step length, may play a critical role in optimising treatment processes.

This study evaluates feature vectors obtained using pre-trained EfficientNet architectures with different classification methods such as support vector machine (SVM), k-nearest neighbours (k-NN) and artificial neural networks (ANN). The result shows that the EfficientNetB2-SVM model exhibits the best performance.

B. Contribution of Literature

The contribution of the study to the literature can be summarised as follows:

Detection of ataxia using sole pressure distribution signals, especially in examining the symptoms of walking ataxia;

Using a type of data that has not been used before and deep learning methods to process this data;

Providing automatic results for clinical evaluations by eliminating problems in manual measurements.

II. Material and Method

A. Data

In this study, a dataset comprising a total of 105 individuals was utilized, consisting of 43 volunteers diagnosed with ataxic Multiple Sclerosis (MS) and 62 healthy participants. The subjects sought consultation at the Neurology Department of Fırat University Hospital and were diagnosed with definite MS based on the McDonald criteria. All procedures adhered to the principles sanctioned by the Fırat University Non-Interventional Research Ethics Committee and explicit written informed consent was obtained from all participants. The ataxia condition of each participant was evaluated using the Ataxia Rating and Rating Scale (SARA) [25].

The Win-Track pressure platform was used to take an image of the sub-floor pressure distribution of each patient during walking. The Win-Track platform (MEDICAPTEURS Technology, France) is a tool that measures plantar pressure and gait parameters during barefoot walking. Its dimensions are 1610 mm × 652 mm × 30 mm (length/width/height). The platform contains 12 288 sensors of resistive type. The dimensions of the sensors are 7.8 mm × 7.8 mm, and the capture frequency of the apparatus is 200 images/second. Dynamic recording records foot progress on the platform throughout the gait cycle. Figure 1 shows gait phases and used terminologies to partition the phases. Table I contains the parameters used in the gain stages and their definitions.

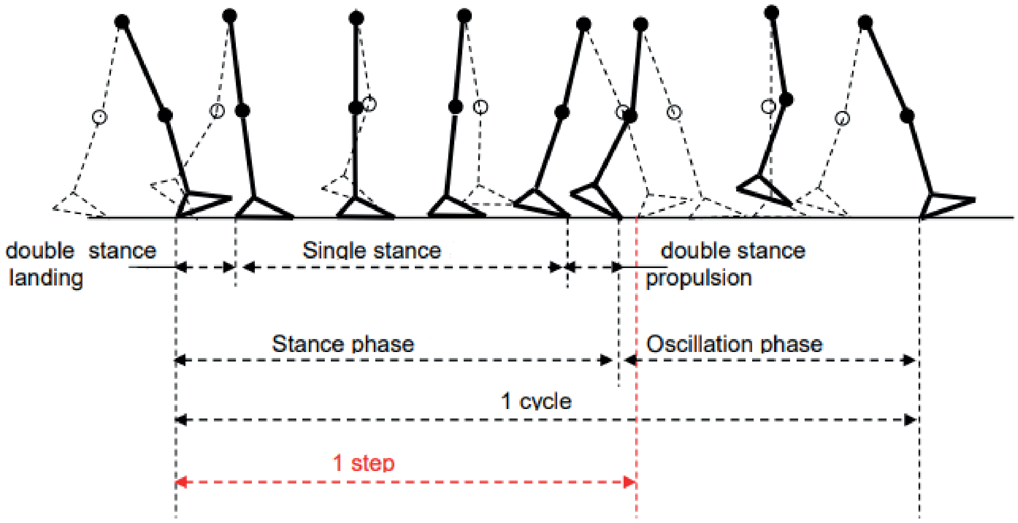


Fig. 1. Gait phases and used terminologies to partition the phases.

TABLE I
PARAMETERS USED IN THE GAIN STAGES AND THEIR DEFINITIONS

	Parameter	Definition
1	Step duration and length	Timing and distance between the heel strike of one foot and the heel strike of the other foot.
2	Gait cycle duration and length	Timing and distance between the heel strike of one foot and the next heel strike of the same foot.
3	Single stance duration	Duration of the portion of the gait cycle when only one foot is in contact with the ground (around 40 % of the cycle).
4	Double stance duration	Timing when both feet are in contact with the ground.
5	Swing duration	Time during which one foot is off the ground.
6	Stride duration	Time between the 1st contact on the ground and the last contact on the ground of the 2nd step for the same foot.

Three practice attempts were carried out, during which participants were positioned at a distance to ensure recording of all three footsteps. Throughout the entire procedure, participants were instructed to maintain a forward gaze and walk at their preferred pace on the platform to avoid intentional targeting. Plantar pressure distribution images and plantar pressure distribution signals were recorded for analysis for each participant. Figure 2 shows the plantar pressure distribution images of PwMS. Table II shows the times of left foot, right foot, double support and simple support.

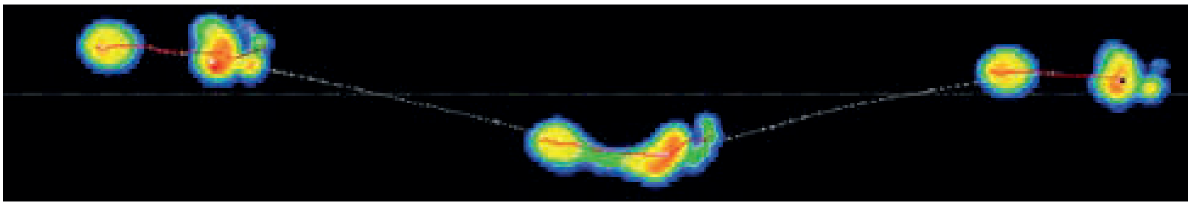
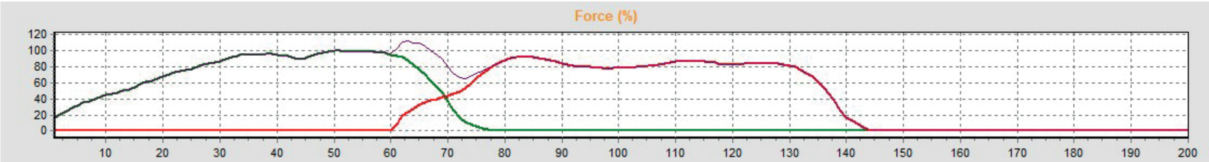


Fig. 2. The plantar pressure distribution images of PwMS.

TABLE II
THE TIMES OF LEFT FOOT, RIGHT FOOT, DOUBLE SUPPORT AND SIMPLE SUPPORT

Left foot	1300 ms			970 ms	
Right foot		860 ms			
Double support		260 ms		210 ms	
Simple support			390 ms		

Fig. 3. Plantar pressure distribution signals for individuals with MS.



(a)

(b)

Fig. 4. a) Plantar pressure distribution in PwMS; b) Plantar pressure distribution in PwMS of a healthy subject.

In Fig. 3, there are three different coloured signals. Among the signals in the image, the red signal shows the left foot, the green signal the right foot, and the purple signal alternately shows the double support, single support and swing phase parameters. Left foot shows the duration of the first foot strike compared to the entire time of walking across the platform. The right foot shows the duration of the foot strike of the other foot compared to the entire time of walking along the platform. Double support shows the phases where both feet are on the platform at the same time. These graphs represent the impact force for each foot when both feet are on the platform at the same time, using the colours assigned to each foot in the "phases of the gait cycle" section. Figure 4 shows exemplary signal showing plantar pressure distribution in a patient with minimally impaired MS and in a healthy subject.

B. The Proposed Method

Convolutional neural network is one of the most widely used deep learning models today. CNN models are used in many areas such as object recognition, signal and image processing [27]. In this study, it is aimed to detect ataxia in PwMS using pre-trained EfficientNet models with gait pressure distribution signals. The feature maps were extracted from the plantar pressure distribution signal images of individuals with the EfficientNet network and classified by SVM, KNN and ANN algorithms. The diagram of the proposed decision support system is shown in Fig. 5. Feature vectors of each plantar pressure distribution image were obtained from the fully connected layer of the model. Then, the obtained feature vectors were classified by giving them to classical machine learning algorithms. The data set was randomly separated for training and testing (70–30 %).

The EfficientNet model was preferred in this article because it can achieve better performance with fewer parameters, is scalable, and can adapt to data sets of different sizes. Images containing walking pressure signals were used as input data of the EfficientNet model, so feature vectors were obtained as output from the model using the transfer learning method. The EffcientNet network has been proposed to more effectively determine the breadth and depth of CNN architectures [26]. To create the optimal architecture for EfficientNet, the width, depth and resolution parameters are scaled. EfficientNet is available in eight different versions, from B0 to B7, and each model is characterised by depth (α), width squared (β), and resolution (γ) parameters. Depth (α): This parameter, which expresses the depth of the network, is defined by the number of layers in the deep neural network. High Depth value is chosen so that the model can learn more complex features, but it requires more computational power.

$$\text{Output Channels} = \text{Inputs Channels} \times \alpha \tag{1}$$

Width squared (β): This parameter, which expresses the width of the network, is the number of filters in each layer in the neural network. As the width increases, the learning capacity of the model increases because more filters in each layer can learn more features.

$$\text{Width} = \sqrt{\beta} \tag{2}$$

Resolution (γ): This parameter expresses the resolution of the input images. Higher γ values mean higher resolution images. Choosing this parameter high will require more processing power and memory.

$$\text{Input size} = \text{Original size} \times \gamma \tag{3}$$

SVM is one of the classification methods that aims to find the best hyperplane that divides a space into two with known positive and negative samples. It is frequently used in the classification of time series, face recognition applications, and biological data processing of medical diagnoses. The k-NN algorithm is one of the supervised learning algorithms that is easy to implement. The algorithm makes classification using data from a sample set with specific classes. The distance of the new data to be included in the data set is calculated according to the existing data, and k nearest neighbours are checked [27]. ANN have emerged by imitating the workability of the human brain. The backpropagation algorithms are used to update parameters in artificial neural networks. The delta rule is a method that allows the weights to be changed by reflecting some of the difference between the target values and the output values back to each training cell, while training the backpropagation network, and by repeating this process a certain number of times, the error reaches the minimum value [28]. In order to have a homogeneous classification, the cross-validation method was used at the end. The cross-validation method is a statistical method used to obtain objective and more accurate results on data that the model does not see. In this study, the *k* value was determined as 5.

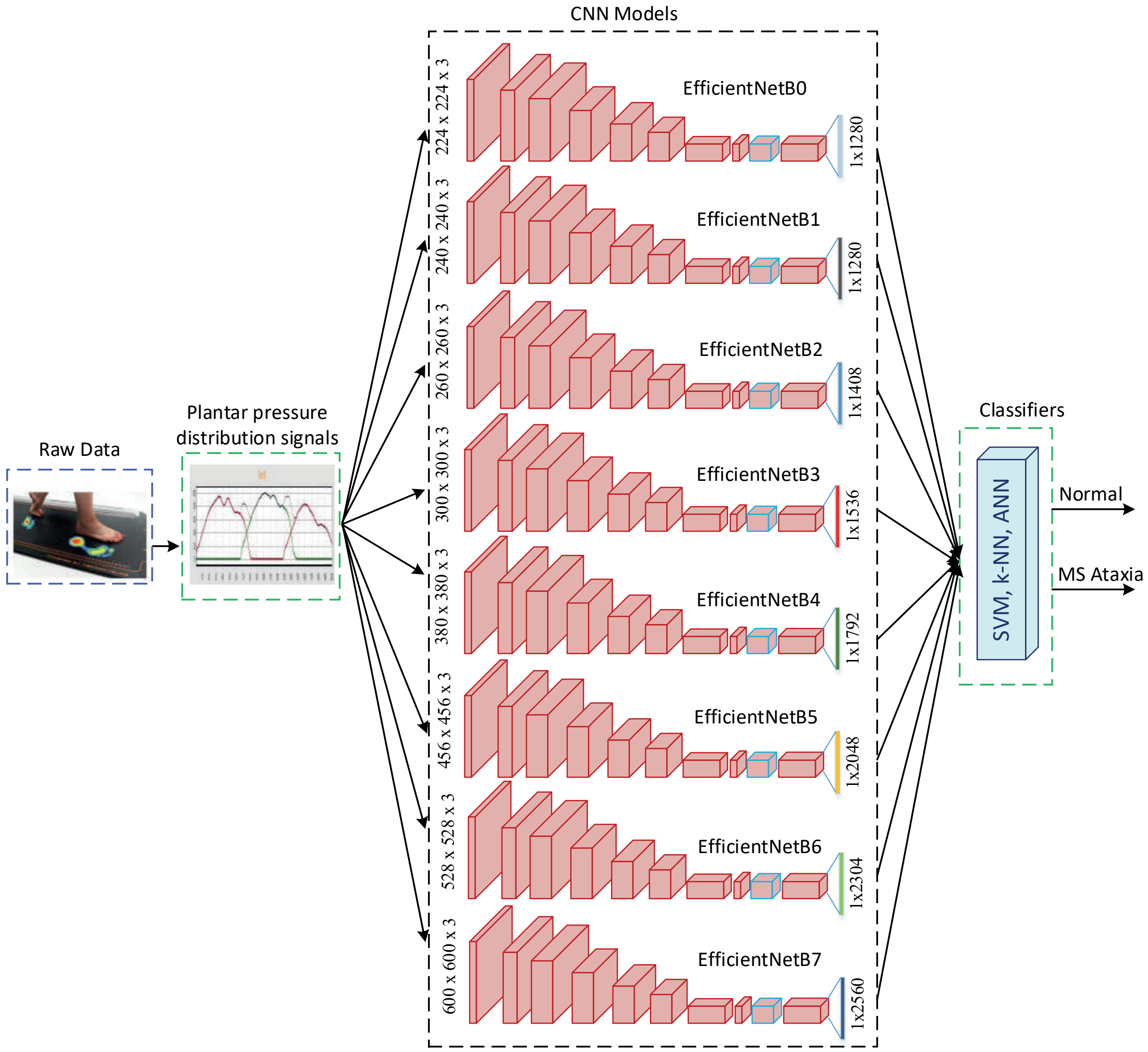


Fig. 5. The proposed decision support system.

III. Results and Findings

The study was carried out on a 64-bit operating system computer with Intel(R) Core(TM) i7-9750H CPU @ 2.60 GHz, NVIDIA Corporation Geforce GTX 1050 and Matlab R2021a.

The confusion matrix shows how accurately the classification success of the model is predicted. The classification performances of the models were evaluated using precision, sensitivity, specificity, and F1 measure metrics. Precision alone is not sufficient as it is calculated by the ratio of the areas we estimated correctly to the total dataset. Sensitivity measures how often a test gives an accurate result for people with the condition being tested, while specificity measures the ability of a test to produce an accurate negative result for people who do not have the condition being tested. Therefore, they should all be evaluated together. The methods and formulas of the metrics used are given below. Table III shows True Positive (TP): Number of MS patients predicted correctly, False Negative (FN): Number of MS patients predicted as healthy, True Negative (TN): Number of individuals who are healthy and predicted as healthy, False Positive (FP): Shows the number of individuals who are healthy but estimated to have MS. In Table IV, the results obtained with the performance evaluation metrics, models and classifiers are given.

TABLE III
PERFORMANCE EVALUATION METRICS

Metrics	Formulas
Accuracy (Acc)	$(TP + TN)/(TP + TN + FN + FP)$
Sensitivity (Sen)	$TP/(TP + FN)$
Specificity (Spe)	$TN/(TN + FP)$
F1 Score	$2TP/(2TP + FN + FP)$

TABLE IV
CLASSIFICATION RESULTS

	Model	Acc (%)	Std (%)	Sen (%)	Spe (%)	F1 (%)
	EfficientNetB0	86.90	±0.1	84.21	89.13	85.33
	EfficientNetB1	85.71	±0.1	84.09	87.50	86.04
	EfficientNetB2	**88.09**	**±0.1**	**80.55**	**93.75**	**85.29**
SVM	EfficientNetB3	86.90	±0.1	78.37	93.61	84.05
	EfficientNetB4	84.52	±0.1	75	91.66	80.59
	EfficientNetB5	82.14	±0.1	80.55	83.33	79.45
	EfficientNetB6	79.76	±0.1	64.51	88.67	70.17
	EfficientNetB7	85.71	±0.1	80.64	88.67	80.64
	EfficientNetB0	78.57	±0.1	75	82.50	78.57
	EfficientNetB1	76.19	±0.02	77.50	75	75.60
	EfficientNetB2	80.95	±0.04	90	72.72	81.81
KNN	EfficientNetB3	79.76	±0.02	89.47	71.73	80
	EfficientNetB4	79.76	±0.1	77.27	82.50	80
	EfficientNetB5	78.57	±0.02	93.54	69.81	76.31
	EfficientNetB6	76.19	±0.02	78.94	73.91	75
	EfficientNetB7	77.38	±0.0	85	70.45	78.16
	EfficientNetB0	85.71	±0.04	79.54	92.50	85.36
	EfficientNetB1	85.71	±0.1	72.97	95.74	81.81
ANN	EfficientNetB2	85.71	±0.06	90	81.81	85.71
	EfficientNetB3	82.14	±0.07	64.86	95.74	76.19
	EfficientNetB4	72.61	±0.05	41.66	95.83	56.60
	EfficientNetB5	77.38	±0.08	83.33	72.91	75.94
	EfficientNetB6	82.14	±0.08	80.64	83.01	76.92
	EfficientNetB7	78.57	±0.1	59.45	93.61	70.96

As can be seen in Table IV, the features extracted with EfficinetNet are classified with higher accuracy with the SVM classifier. When the model and classifiers used were analysed, the highest accuracy, sensitivity and specificity values were reached with the EfficientNetB2 model (88.09 % Acc, 80.55 % Sen, 93.75 % Spe, 85.29 % F1 Score) classified with the SVM classifier.

Figure 6 shows the confusion matrix of the EffcientNet model classified with the best performing SVM classifier.

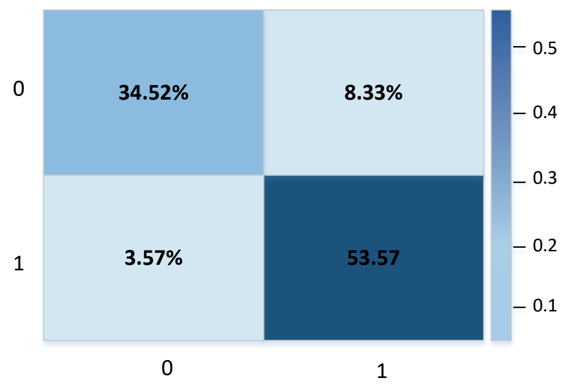


Fig. 6. EfficientNetB2 model confusion matrix classified with SVM classifier, 0:MS 1: Normal.

As depicted in Fig. 6, the standard deviation (std) values derived from the employed classifiers exhibit notable consistency. While the std values from SVM demonstrated a broader range compared to NN, they still remained considerably lower than those of other classifiers. It is widely acknowledged that a smaller std implies greater homogeneity in observations, indicating a smaller difference between values and rendering the data more reliable. Consequently, the obtained std values in this study suggest that the classification methods are proficient in achieving accurate classifications with the available data.

In our investigation, the most superior classification performance was demonstrated by EfficientNetB2-SVM. The effectiveness of EfficientNetB2 can be attributed to its optimisation in terms of specific width, depth, and resolution scales, coupled with the notable success of SVM in binary classification. However, it is crucial to recognise that the classification success of deep learning models is contingent upon various factors, including the dataset size, distinctiveness of the data, data quality, and model parameters. Additionally, augmenting the volume of data stands out as a pivotal criterion for enhancing accuracy values.

IV. DISCUSSION

Ataxia, characterised by gait disturbance, is a common symptom in MS patients, and early diagnosis is crucial for effective treatment. This study presents a deep learning-based approach using plantar pressure distribution signals to detect ataxia in PwMS. In this approach, the classification model based on the B0 to B7 models of the pre-trained EfficientNet architecture was used. The results showed that the proposed method achieved a high level of classification accuracy (see Table IV).

One of the striking aspects of the study is the use of signal data instead of image data in detecting ataxia in MS. Features were extracted from 105 images containing plantar pressure distribution signals using pre-trained EfficientNet architectures.

The resulting feature vectors were classified using SVM, k-NN and ANN. The results reveal that the SVM classifier outperforms others by achieving 88.09 % accuracy, 80.55 % sensitivity, 93.75 % specificity, and 85.29 % F1 Score. These measurements demonstrate that the proposed model has a promising ability to accurately identify ataxia in PwMS based on plantar pressure distribution signals.

Limited research exists in the literature that assesses ataxia and gait parameters in MS patients, with the majority of these studies focusing on individuals with moderate to severe disabilities. It is widely accepted that ataxia is not indicated by low EDSS scores and that increasing EDSS scores are associated with an increased prevalence of pyramidal symptoms (spasticity, muscle weakness) and increased scores of other functional systems. Unlike previous studies that often concentrated on patients with high EDSS scores, our research encompassed individuals with EDSS scores of ≤ 2.5. The remarkably low mean EDSS score among our patients highlights the homogeneity of the studied patient group. Furthermore, the diagnostic model introduced in this study deviates from those in the existing literature by identifying ataxia through the analysis of plantar pressure distribution signals, combining clinical methods with engineering techniques.

Table V in the literature outlines ataxia studies conducted using machine learning systems. These investigations aimed to assess the diagnostic accuracy of neurological gait disorders by employing various automatic pattern recognition techniques such as K-NN, Naive Bayes, ANN, and SVM. Different methodologies and classifiers across studies have resulted in significant differences in accuracy rates. In particular, while plantar pressure distribution signal data is classified with classical machine learning algorithms, CNN models have been applied to plantar pressure images. In addition, hybrid methods using CNN and classical classification algorithms, which can process pressure distribution signals as images, have been used.

The results of these studies show that more complex and powerful classification methods can be effective when both signal and image data are used. However, given the methodological differences in each study and the data sets used, further research is needed to generalize these results. Additionally, it is important to consider factors such as dataset size, feature selection, and classifiers' hyper-parameters in more detail in future studies.

TABLE V

COMPARISON OF THE MODEL WITH STATE-OF-THE-ART TECHNIQUES

Study	Dataset	Method	Accuracy Rate	Signal	Image
Le Moyne et al. [11]	MS Ataxia Signal	ML	74	√	
Kaur et al. [16]	MS Ataxia Signal	ML, ANN	94.02	√	
Hu et al. [18]	MS Ataxia Signal	SVM	81	√	
Jannat et al. [20]	MS Ataxia Image	CNN, SVM	98.24		√
Shrwan et al. [21]	MS Ataxia Image	CNN	99.02		√
Kaya et al. [23]	MS Ataxia Image	CNN SVM, KNN, ANN	95.12		√
Sesli at al. [24]	MS Ataxia Signal Image	CNN SVM, KNN, ANN	85.71		√
Proposed Method	MS Ataxia Signal Image	EfficientNet, SVM, KNN, ANN	88.09		√

V. CONCLUSIONS

This study aimed to diagnose ataxia at an early stage by using signal images of PwMS containing plantar pressure distribution. The classification model based on the B0 to B7 models of the pre-trained EfficientNet architecture was used. The highest performance was obtained in the EfficientNetB2 model classified with the SVM classifier. The study was able to provide an autonomous decision support system for ataxia detection in PwMS. Experimental results showed that plantar pressure distribution signals can be used instead of plantar pressure distribution images in MS ataxia detection. This way, a standardized solution has been brought to the problem, away from human error. Based on the performance of the study, it was concluded that it could be applied in practice. Ataxia, which is not yet symptomatic and clinically unrecognised, can be detected in the early period and can be recommended as an auxiliary system to the physician.

REFERENCES

[1] W. I. McDonald *et al*., "Recommended diagnostic criteria for multiple sclerosis: guidelines from the International Panel on the diagnosis of multiple sclerosis," *Annals of Neurology*, vol. 50, no. 1, pp. 121–127, Jul. 2021. https://doi.org/10.1002/ana.1032

[2] M. Finlayson, *Multiple Sclerosis Rehabilitation: From Impairment to Participation*, 1st ed. CRC Press, 2012. https://doi.org/10.1201/b12666

[3] F. Bethoux and S. Bennett, "Evaluating walking in patients with multiple sclerosis: which assessment tools are useful in clinical practice?" *International Journal of MS Care*, vol. 13, no. 1, pp. 4–14, 2011. https://doi.org/10.7224/1537-2073-13.1.4

[4] U. Givon, G. Zeilig, and A. Achiron, "Gait analysis in multiple sclerosis: characterization of temporal-spatial parameters using GAITRite functional ambulation system," *Gait & Posture*, vol. 29, no. 1, pp. 138–142, Jan. 2009. https://doi.org/10.1016/j.gaitpost.2008.07.011

[5] J.G. Nutt, F.B. Horak, and R.B. Bloem, "Milestones in gait, balance, and falling," *Movement Disorders: Official Journal of the Movement Disorder Society*, vol. 26, no. 6, pp. 1166–1174, May 2011. https://doi.org/10.1002/mds.23588

[6] C. Heesen, J. Böhm, C. Reich, J. Kasper, M. Goebel, and S.M. Gold, "Patient perception of bodily functions in multiple sclerosis: gait and visual function are the most valuable," *Multiple Sclerosis Journal*, vol. 14, no. 7, pp. 988–991, 2008. https://doi.org/10.1177/1352458508088916

[7] M. G. Benedetti, R. Piperno, L. Simoncini, P. Bonato, A. Tonini, and S. Giannini, "Gait abnormalities in minimally impaired multiple sclerosis patients," *Multiple Sclerosis Journal*, vol. 5, no. 5, pp. 363–368, 1999.
[8] C. L. Martin *et al*., "Gait and balance impairment in early multiple sclerosis in the absence of clinical disability," *Multiple Sclerosis Journal*, vol. 12, no. 5, pp. 620–628, 2006. https://doi.org/10.1177/1352458506070658
[9] E. Morel *et al*., "Gait Profile Score in multiple sclerosis patients with low disability," *Gait & Posture*, vol. 51, pp. 169–173, Jan. 2017. https://doi.org/10.1016/j.gaitpost.2016.10.013
[10] J. A. DeLisa, *Gait Analysis in the Science of Rehabilitation* (vol. 2). Diane Publishing, 1998.
[11] R. LeMoyne, F. Heerinckx, T. Aranca, R. De Jager, T. Zesiewicz, and H.J. Saal, "Wearable body and wireless inertial sensors for machine learning classification of gait for people with Friedreich's ataxia," in *2016 IEEE 13th International Conference on Wearable and Implantable Body Sensor Networks (BSN)*, San Francisco, CA, USA, Jun. 2016, pp. 147–151. https://doi.org/10.1109/BSN.2016.7516249
[12] D. Phan, N. Nguyen, P.N. Pathirana, M. Horne, L. Power, and D. Szmulewicz, "A random forest approach for quantifying gait ataxia with truncal and peripheral measurements using multiple wearable sensors," *IEEE Sensors Journal*, vol. 20, no. 2, pp. 723–734, Sep. 2019. https://doi.org/10.1109/JSEN.2019.2943879
[13] A. Prochazka, O. Dostal, P. Cejnar, H.I. Mohamed, Z. Pavelek, M. Valis, and O. Vysata, "Deep learning for accelerometric data assessment and ataxic gait monitoring," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 29, pp. 360–367, Jan. 2021. https://doi.org/10.1109/TNSRE.2021.3051093
[14] W. Ilg, J. Seemann, M. Giese, A. Traschütz, L. Schöls, D. Timmann, and M. Synofzik, "Real-life gait assessment in degenerative cerebellar ataxia: Toward ecologically valid biomarkers," *Neurology*, vol. 95, no. 9, pp. e1199–e1210, Jul. 2020. https://doi.org/10.1212/WNL.0000000000010176
[15] F. Bilek, F. Balgetir, C.F. Demir, G. Alkan, and S.S. Tuncer, "Quantitative assessment of ataxia in multiple sclerosis patients using spatiotemporal parameters: A relief-based machine learning analysis," *Physikalische Medizin, Rehabilitationsmedizin, Kurortmedizin*, vol. 31, no. 6, pp. 367–376, 2021. https://doi.org/10.1055/a-1512-4858
[16] R. Kaur, Z. Chen, R. Motl, M.E. Hernandez, and R. Sowers, "Predicting multiple sclerosis from gait dynamics using an instrumented treadmill: A machine learning approach," *IEEE Transactions on Biomedical Engineering*, vol. 68, no. 9, pp. 2666–2677, Sep. 2021. https://doi.org/10.1109/TBME.2020.3048142
[17] B.M. Meyer, L.J. Tulipani, R.D. Gurchiek, D.A. Allen, L. Adamowicz, D. Larie, and R.S. McGinnis, "Wearables and deep learning classify fall risk from gait in multiple sclerosis," *IEEE Journal of Biomedical and Health Informatics*, vol. 25, no. 5, pp. 1824–1831, May 2021. https://doi.org/10.1109/JBHI.2020.3025049
[18] W. Hu, O. Combden, X. Jiang, S. Buragadda, C.J. Newell, M.C. Williams, A.L. Critch, and M. Ploughman, "Machine learning classification of multiple sclerosis patients based on raw data from an instrumented walkway," *Biomedical Engineering Online*, vol. 21, Mar. 2022, Art. no. 21. https://doi.org/10.1186/s12938-022-00992-x
[19] M. Alaqtash, T. Sarkodie-Gyan, H. Yu, O. Fuentes, R. Brower, and A. Abdelgawad, "Automatic classification of pathological gait patterns using ground reaction forces and machine learning algorithms," in *2011 Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, Boston, MA, USA, Aug. 2011, pp. 453–457. https://doi.org/10.1109/IEMBS.2011.6090063
[20] S. A. Jannat, T. Hoque, N. A. Supti, and M. A. Alam, "Detection of multiple sclerosis using deep learning," in *2021 Asian Conference on Innovation in Technology (ASIANCON)*, PUNE, India, Aug. 2021, pp. 1–8. https://doi.org/10.1109/ASIANCON51346.2021.9544601
[21] R. Shrwan and A. Gupta, "Classification of pituitary tumor and multiple sclerosis brain lesions through convolutional neural networks," *IOP Conference Series: Materials Science and Engineering*, vol. 1049, no. 1, 2021, Art. no. 012014. https://doi.org/10.1088/1757-899X/1049/1/012014
[22] Z. Ekşi, M. E. Özean, A. Aralaşmak, E. Dandil, and M. Çakiroğlu, "Automatic computer-aided detection of Multiple Sclerosis (MS) lesions on MR images," in *2015 19th National Biomedical Engineering Meeting (BIYOMUT)*, Istanbul, Turkey, Nov. 2015, pp. 1–4. https://doi.org/10.1109/BIYOMUT.2015.7369443
[23] M. Kaya, M. Karakuş, and S. A. Tuncer, "Detection of ataxia with hybrid convolutional neural network using static plantar pressure distribution model in patients with multiple sclerosis," *Computer Methods and Programs in Biomedicine*, vol. 214, Feb. 2022, Art. no. 106525. https://doi.org/10.1016/j.cmpb.2021.106525
[24] A. Sesli, S.A. Tuncer, and F. Bilek, "Plantar Basınç Dağılımı Sinyalleri Kullanılarak Erken MSlilerde Ataksinin Hybrt CNN Modelleri ile Belirlenmesi," *Avrupa Bilim ve Teknoloji Dergisi*, *Ejosat Special Issue 2021 (ICAENS)*, pp. 579–583, 2021.
[25] A., Marquer, G. Barbieri, and D. Pérennou, "The assessment and treatment of postural disorders in cerebellar ataxia: a systematic review," *Annals of Physical and Rehabilitation Medicine*, vol. 57, no. 2, pp. 67–78, Mar. 2014. https://doi.org/10.1016/j.rehab.2014.01.002
[26] M. Tan and Q. Le, "EfficientNet: Rethinking model scaling for convolutional neural networks," in *International Conference on Machine Learning*, vol. 97, 2019, pp. 6105–6114. https://proceedings.mlr.press/v97/tan19a.html
[27] V. Vapnik, "The support vector method of function estimation," in *Nonlinear Modeling*, Springer, 1998, pp. 55–85. https://doi.org/10.1007/978-1-4615-5703-6_3
[28] C. He, M. Ma, and P. Wang, "Extract interpretability- accuracy balanced rules from artificial neural networks: A review," *Neurocomputing*, vol. 387, pp. 346–358, Apr. 2020. https://doi.org/10.1016/j.neucom.2020.01.036

Taner Tuncer is a Professor in Computer Engineering, Firat University, Turkey. He has received a PhD degree at Firat University, Turkey. He has published more than 30 papers in various international/national journals. His research interest includes image processing and deep learning etc.
E-mail: ttuncer@firat.edu.tr
ORCID iD: https://orcid.org/0000-0003-0526-4526

Aslı Sesli graduated from Fırat University Software Engineering Department in 2022. She started her master's degree in 2022. Her research interests include medical image processing and deep learning.
Email: aslisesli@firat.edu.tr

Seda Arslan Tuncer graduated from the Faculty of Engineering at Fırat University in 2005. She started her postgraduate studies at the Faculty of Computer Engineering of Firat University and graduated with a Master degree in 2008. In 2010, she continued her Doctoral studies at the Faculty of Electrical and Electronics Engineering of Kahramanmaraş Sütçü İmam University and graduated in 2014. Between December 2009 and 2010, she worked as an Expert at Kahramanmaraş Sütçü İmam University. Between 2010 and 2014, she worked as a Lecturer at the Department of Computer Science at Fırat University. In December 2014, she started working as a Lecturer at the Department of Software Engineering at Firat University. Currently she is an Associate Professor.
E-mail: satuncer@firat.edu.tr
ORCID iD: https://orcid.org/0000-0001-6472-8306