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**Research Article**

# Towards artificial intelligence of things: Unsupervised machine learning approach for foot-type classification

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## ABSTRACT

Several types of foot deformities, including flatfoot, hammer toe, bunions, etc., can be acquired or congenital. They are considered one of the main causes of body imbalance, leading to fatigue and pain during daily activities. Early detection of flatfeet and treatment plans are crucial parts to eliminate or reduce the complications. Hence, accurate diagnoses of foot distortion are needed for an evaluation and proper treatment. The measurement of foot distorted needs specialized staff however; the objectivity of the diagnosis may be insufficient for professional medical personnel to assess foot deformations. Integrating artificial intelligence with the Internet of things technology can enable device-to-device to diagnose and detect over time, allowing devices to be more intelligently, providing accurate results, and more efficiency. Therefore, the aim of this manuscript is to present the application of Internet of things based on artificial intelligence technology that can diagnose and detect the flatfeet types. It is a user-friendly application that can be managed by both patients and physicians to record the stages of flatfeet and preliminary check for possible gait problems in daily life. The proposed method includes multiple processes such as data acquisition, and data preprocessing based on Internet of things device. Unsupervised learning method is used to analyse and discover hidden patterns from the proposed device, and then patient classification, helping to personalize treatments and improve healthcare outcomes. The k-means clustering method is applied to segment and cluster the feet images in order to classify foot deformation types into normal, concave and flatfeet and find hidden patterns in the dataset. The elbow method is implemented to define the number of clusters, and subjects are grouped based on different attributes. According to the research findings, the proposed method can classify the foot-types with high accuracy up to 97.3% on the testing experiment. Additionally, the present work enables real-time patient monitoring, early disease detection, and thus personalized treatment plans.

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## INTRODUCTION

Flatfeet, also known (fallen arches), is a common condition and a congenital problem with the foot shape, where people have either no arch in both feet/or one foot or arch is very low [1] see Figure 1 [2]. This issue causes pressure from the ground in specific parts of the foot, which may lead to permanent deformation of the foot resulting in back pain, knee joint or both [3]. Furthermore, the feet can easily distort because of wrong walking posture, stretched, torn tendons, and wearing unsuitable shoes, thus, foot distortion may cause fatigue and deform the spine and pain while walking [4, 5], thus, accurate diagnosis of foot distortion is needed.

In recent decades, there has been a significant rise in interest in Internet of Things (IoT) systems and Artificial Intelligence (AI) technique. The IoT technology is a network of physical devices that can communicate with each other, exchange information, and transmit data to the intelligent systems for more analysis [6]. The AI technology has become more popular and attracted scientists and researchers from different backgrounds as it plays an essential role in various aspects of life including education, industrial, healthcare, etc. [7-9]. The AI methods make the overall system more precise and can control and automate the routine tasks in the healthcare as a result improves the quality of the healthcare [10, 11]. The combination of AI and IoT applications can improve human-machine interactions and enhance data management and analytics, especially in healthcare field [12, 13]. Machine learning (ML) is a subset of AI technique and it is one of the most important methods that is used to draw insights from huge datasets to promote clinicians' decision-making, early detection of diseases, improve the accuracy of diagnoses and patient outcomes [14,15]. Unsupervised learning is a type of machine learning where methods use untagged data (input data only) and automatically learns and detects the structure or pattern in the datasets without any supervision to predict the outcomes [16, 17]. Therefore, in this section, the paper introduces several studies that are closely related to the contribution of this article.

Several studies for flatfeet detection have been presented by various researchers over the last decade or so. Most of the works included X-ray radiographs or using one of the AI techniques [18]. According to [19], the unsupervised learning has many applications in healthcare field such as anomaly detection, group segmentation, image and video analysis, etc. This has led the researchers to label their data after clustering and insightful conclusions for further research and analysis. In healthcare, analysis and anomaly detection are becoming increasingly important to provide accurate in decisions [15]. A few studies have been carried out on unsupervised machine learning methods for abnormality detection, especially, the cooperation between AI and IoT techniques. In [20] the classification image is done by using one of several statistical routines commonly called clustering, where categories of pixels are classified based on their properties. Such technique is utilized in healthcare to explore and analyse thousands of different data then extract useful information and provide timely risk scores. This data can then be processed by one of ML methods in order to improve decision-making and patient care. However, several studies for flatfeet cases have been reported by various researchers over the last decade or so. Previous research [21] has explored the risk features of flatfoot in children. Such approach showed that the flatfeet can cause pain in the ankles and knees, improper gait, and raised injury risk during sports, etc. In addition, several studies have

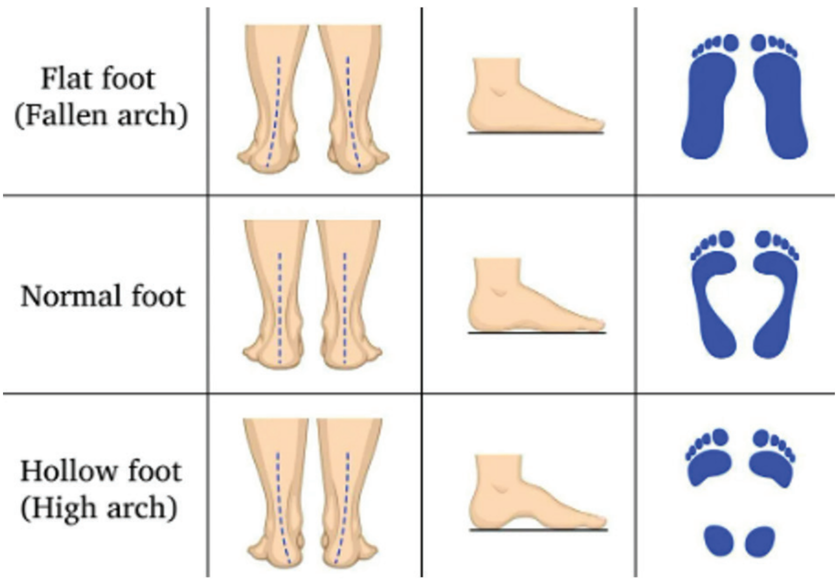


**Figure 1.** Deformation of the foot [2] [Open Access].

indicated that, with the support of AI, healthcare can improve decision-making, automated routine tasks and produce medical insights that were previously unavailable. In [22], authors have introduced foot arch classification using machine learning image classification. This method aimed to develop mathematical models in order to reduce the time and improve the accuracy of the foot arch classification from foot pressure scanning image. This approach uses SIDAS scanner device for feet classification. Authors compared the performance of different ML methods.

However, this method was applied on 200 foot images. The proposed system is generally expensive and may not be fit for large scale of images. Classifying flatfoot disease based on wrapper-based feature selection was done in [23]. The purpose of this study is to design wearable sensing shoe that can be used by clinicians and patients for diagnosing flatfeet and monitoring the progress of flatfeet treatment. The study used scaled PCA and a deep neural network. The results showed that the wearable device has a high accuracy in terms of diagnosing and monitoring cases. In a different study [24], authors presented flatfeet for the ages from 5 to 6 years old and history of delay walking. The study suggested a wet foot print test, which means the child standing in front of coloured ink pot and then stamp their feet on the sheet of paper. The footprints then are evaluated by a physiotherapist. Authors in [25] introduced an innovative unsupervised data-driven approach for the identification of foot deformities, which is grounded in the analysis of plantar pressure measurements acquired through the utilization of resistive pressure sensors. The findings of this study indicated that the proposed methodology demonstrated favorable results, thereby exceeding the performance of widely utilized monitoring frameworks. However, the studies above did not manage, gather and control the data from a remote distance. Another study in [26], authors analyzed the skeletal characteristics of flat feet using 3D foot scanning and digital footprint analysis. This method introduces a cost-effective method for assessing foot shape without specialized equipment. This study investigates the correlation between 3D foot features and footprint measurements to predict flatfoot severity using footprint analysis of 3D features. A new investigation in [27], authors introduced an innovative insole based on plantar pressure for adults with flexible flatfeet. The proposed study enhances the distribution of plantar pressure and the efficiency of gait in adults exhibiting flexible flatfoot conditions, and possesses potential for integration into clinical practice.

Several studies have documented applying deep learning techniques to medical data to enhance medical treatment outcomes and examination accuracy [28]. Especially, researches that have incorporated deep learning techniques with the foot pressure data to diagnose flatfeet issue which have been recorded recently in [29,30]. According to an investigation by [4], authors introduced a deep learning model for feet type classifications using numerical and image foot pressure data. Such data is used to generate a fine-tuned (VGG16) and (K-NN) algorithms. The proposed classification gives the objectivity of diagnosis for feet distortion and obtains accuracy with f1 score of 92.55% by using 96 subjects. A neural network was identified and modelled to execute classification on the foot data to diagnose these data individually whether the feet have flatfeet or not [30]. The proposed method showed that the classification accuracy of both right and left foot data is as high as 85.29 % and 84.31% respectively. In [31], the proposed work introduced a gait feature extraction method for plantar pressure image. Authors located the position of the feet in the image by using localization method based on density-based spatial clustering with noise (DBSCAN) and the k-means clustering algorithm to extract the walking characteristics of stroke patients and compared them with the healthy people in the data.

Although several studies have been carried out on flatfeet causes, to the author's knowledge, there have not been any controlled studies that focuses on combining the AI and IoT technologies to diagnose flatfeet disease over remote distance. The main advantage of IoT technique is to automate sensing, controlling, and reporting things over remote distance. Additionally, the AI technology can dramatically reduce medical errors by enhancing diagnostic accuracy and providing decision support for experts. Thus, in this context, the technical novelty of this work focuses on the integration of AI and IoT application. A smart device is designed using IoT and AI technology to detect congenital foot anomalies e.g. normal, flatfoot, and concave. The function of this device is to collect, process the gathered data and then dispatch it to final destination via internet for further analyses. The proposed study uses one of the popular unsupervised machine learning algorithm in order to detect, analyse and classify foot distortion types. Therefore, the present work can improve the accuracy and reliability of diagnostic outcomes while ensuring objectivity, making it highly applicable for analyzing and designing foot healthcare products based on foot deformation diagnosis results. Additionally, this work can thus be simply and easily used by both doctors and patients remotely to control the progress of flatfeet, and thus personalized treatment plans. The contributions of this paper are summarized as:

- Design and implement an IoT device that can collect the datasets (digital footprints) based on IoT technique for further analysis.
- The IoT system introduces a chance to gather continuous data and send each physical activity to the cloud infrastructure for further analyses.
- Image segmentation is used to divide the visual data into segments in order to improve and identify important features for each image.
- Unsupervised machine learning model is proposed to diagnose and category the foot-type if it has flatfoot or not.

- Unsupervised learning clustering algorithms is introduced to analyse datasets and then clusters unlabelled data by using k-means clustering method.

The remainder of this work is presented as follows: Section II shows the details of proposed system and methods. This section also illustrated data acquisition, pre-processing, and includes the measurement of foot arch index method. Section III introduces the experimental results and comparisons. Finally, section IV concludes the work.

## PROPOSED SYSTEM AND METHODS

This section firstly demonstrates the architecture of proposed method and illustrates the process of building the model. Secondly, the process of design and implement the device is provided in order to capture the images of feet and collect the dataset. After that, the image segmentation based on clustering method is described. Finally, the source of the datasets used for pattern classification is introduced.

### Architecture of the Proposed Method

The proposed system is divided into two main parts: first of all, the proposed system diagnoses the foot type by taking a photo for each foot. The subject stands on the device and then the product scans the footprint in order to classify the foot type based on the segmentation method. One of the key benefits of AI technology in IoT applications is supporting automated processes and improving efficiency. Therefore, the second step of the proposed system is sending foot images to the cloud infrastructure for further analyses and cluster unlabelled datasets in order to find useful insights from these data. Thus, the paper presents an unsupervised learning architecture for the classification of foot-types category that diagnosis the feet into normal, high arch, and flat feet. The experimental method structure is shown in Figure 2. The explanation of the steps of collection and pre-processing data are presented in Figure 3. The model receives the sequence of inputs data (feet images) $x^1$, $x^2$, $x^3$, ……, $x^n$, where n is the number of both feet (right/left). The interpretation stage is to analyse and

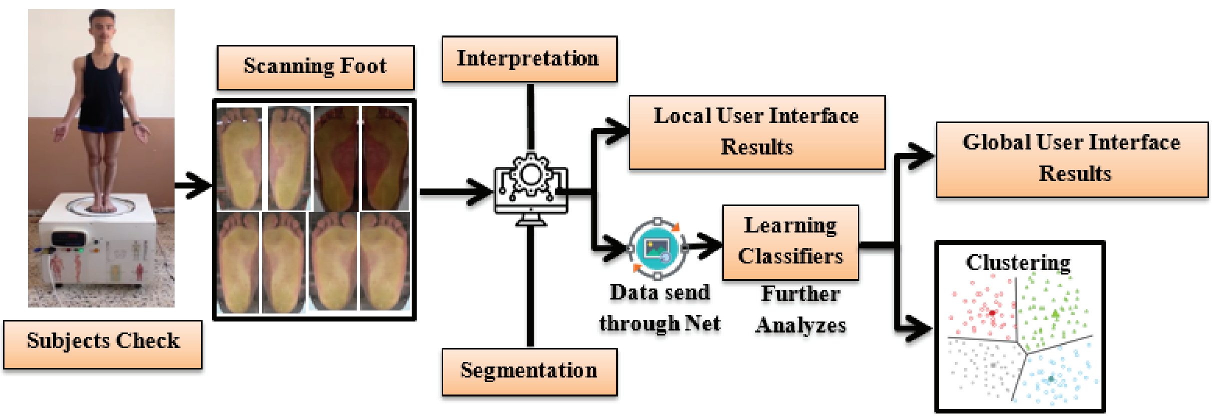


**Figure 2.** The proposed AI based-IoT (AIoT) architecture system.

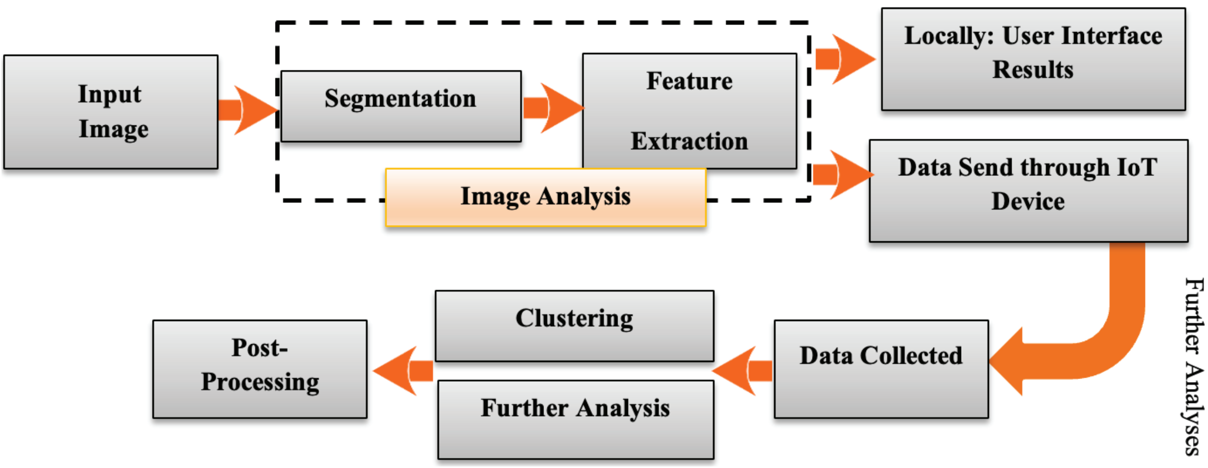


**Figure 3.** Introduces medical image segmentation and AI process steps.

cluster unlabelled data to make a decision based on the proposed algorithm. Thus, the proposed algorithm is aimed to classify and cluster these data into useful data.

**Datasets Acquisition**

This section offers a description of the proposed IoT system that identifies the foot-type, captures the images, and collects the dataset for the proposed AI method. The proposed study aims to design and develop foot healthcare product for general public people and is placed in remote location such as school, street or market in order to diagnose and classify walking-related diseases. The proposed device can be categorized into four main parts: aluminum box, raspberry pi 4 (RasPi), digital camera, and toughened glass. The aluminum box is a small container and made of aluminum, which means it is very low weight in relation. The dimensions of the box are written as width * height * length, (50 * 60 * 50). The RasPi is one of the key learning platforms for IoT applications. It provides complete operating systems (i.e., Raspbian Linux) in a tiny platform for a very low cost [30], and is used as an IoT device for this study. The job of this device is to gather, process the collected data and then dispatch it to the cloud platform over the internet for further analyses. The digital camera is an input device that is connected to the RasPi and captures the digital images. The features of this camera are full HD 1080P coloured, 2-megapixel resolution, and USB driver-free (plug and play). The image dimension is an intensity colour image of size (640 * 480) pixels, (horizontal * vertical) respectively. The camera is provided with USB cabled that is linked to the RasPi. The RasPi and digital camera are linked and built-in inside the aluminum box. While the toughened glass is referred to as tempered is very simply a stronger version of the standard glass that is used on the top of the proposed device. The dimension of the toughened glass height * weight is (4 * 6) mm respectively. The measurement device has a detection area of (300mm * 600mm). Thus, the object can stand barefoot on this detection area (toughened glass). Figure 4 demonstrates the main components of the acquisition datasets.

**Data Pre-Processing**

The purpose of this study is to design and implement IoT foot healthcare products that can be installed in remote area for patient with walking-related diseases and general public people. Furthermore, the proposed study also focuses on the development of unsupervised machine learning algorithm to detect, analyse and classify foot distortion types, thus the developed model collects foot shape (arch foot) and concavity of the foot color. Therefore, only important data such as foot shape and concavity of the foot color are collected. One of the main obstacles in this work, data collection is contained personal health information that is high sensitive and requires specific permissions, thus, even for research purposes; there is a reluctance to disclose it. Moreover, image quality is also an issue that can result in flawed decision-making and accurate results.

In this study, the subjects are 250 males only who voluntarily participated in the experiment through public recruitment. The ages of subjects are divided into two groups (15-30) and (31-50) years old. The subjects were informed about the purpose of the pre-experimental test and they signed an agreement form before taking part in the experiment. The measurements were done under the supervision

**Figure 4.** The main acquisition datasets environment.

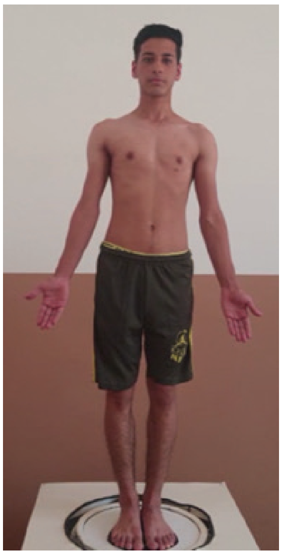

**Figure 5.** Experimental method measurement.

team of the research. Subjects were asked to stand one-by-one in the standing position area on the device, which indicated on the measurement device by both feet in order to take the footprint. Figure 5 introduces the measurement system and data gathered from the subjects by the proposed device. The proposed scheme is categorized into three main methods namely, the measurement of foot arch index, data collection, and feature extraction.

**The Measurement of Foot Arch Index**

Image segmentation plays a crucial role in various fields such as AI, computer vision, robotics, etc. It allows for a detailed understanding and analysis of images by assigning specific labels or categories to individual pixels or regions [32, 33]. In this paper, the footprint is diagnosed into three types and labelled as low (flatfoot), mid (normal), and high (concave). The segmentation techniques depend on modality and dimension of imaging because of the high dependency on factors like disease type and image features.

The arch index is referred to as the ration of the area of the middle footprint to the total area of the footprint. The segmentation techniques depend on quality and dimension of imaging because of the high dependency on many factors including disease type and image features. Thus, the foot arch index measurement is done by dividing the foot area vertical and horizontal and each division is split into three equal sections. The horizontal division section is computed by dividing the total length of the foot (the length between two points, the end of forefoot and heel of the foot) into three equal areas, which are indicated as (A, B, and C) and calculated by Equation 1 and shown in Figure 6 (a). However, the vertical division section is also measured by dividing the total length of the foot into three equal areas, which are indicated as (A, B, and C) and calculated by Equation 1 and shown in Figure 6 (b). The purpose of this division is to measure the affected area and remove unneeded data in order to determine the type of foot whether it is low, mid or high. The image data includes needed and unneeded data where unneeded data may cause deformation of the actual information and get inaccurate results, as well as slowing down the entire process. Therefore, in order to achieve a high accuracy measurement, the proposed model removes undesirable details and just focuses on process image area (PIA) that can diagnose the feet types. Figure 6 (c) shows the PIA part which is absolutely used to detect foot-type and process the results to the final destination via IoT device through the internet for further AI analyses. Thus, the dataset is the collection of the small parts of the feet (right and left) for each subject that are stored and prepared for the purpose of diagnosing flat feet. Figure 6 introduces the raw images of the datasets.

$$\text{Division (d)} = \frac{B}{A+B+C} \tag{1}$$

**Pre-Processing of Image Information**

The subsequent pre-processing steps are taken in this context in order to enhance the accuracy results of data images and reduce the time delay for diagnosing fallen arches. In this study, the authors use one of the popular unsupervised learning techniques that is called K-means algorithm. Such algorithm employs to analyse and cluster unlabelled datasets based on similar and dissimilar objects. It also handles large amounts of information and makes the processes faster without issues. Here the K is the number of clusters of equal variance.

Based on K-means clustering [21, 22], the dataset x = $\{x_1, x_2, \ldots, x_n\}$ in a d-dimensional Euclidean space $R_d$ and A = $\{a_1, a_2, \ldots, a_c\}$ as the cluster centres (c). While z = $[Z_{ik}]_{n*c}$, the $Z_{ik} \in \{0,1\}$is a binary variable value that indicates if the dataset xi belongs to k-th cluster, k = 1,··· ,c. So, the K-means objective function is J(z,A), as:

$$J(z,A) = \sum_{i}^{n} = 1 \sum_{k}^{c} = 1 \; Z_{ik} \, || x_i - a_k||^2 \tag{2}$$

The k-means method is repeated through necessary conditions in order to decrease the J(z, A) with updating equations for c clusters and memberships, respectively, as the follow:

$$a_k = \frac{\sum_{i}^{n}=1 \, zikXij}{\sum_{i=1}^{n} zik} \text{ and} \tag{3}$$

$$Z_{ik} = \begin{cases} 1 & if \;\; || xi - ak||2 = \min_{1 \le k \le c} || xi - ak||2 \\ 0 & otherwise \end{cases} \tag{4}$$

Where $|| x_i - a_k||^2$ denotes the $R_d$ between the cluster centre ($a_k$) and data point ($x_i$).

Usually, normal objects have an arch that is plainly visible when the object stands barefoot on the toughened glass. This arch is caused by the normal slight pull of the tendons in the objects feet. This poses a gap between the glass and

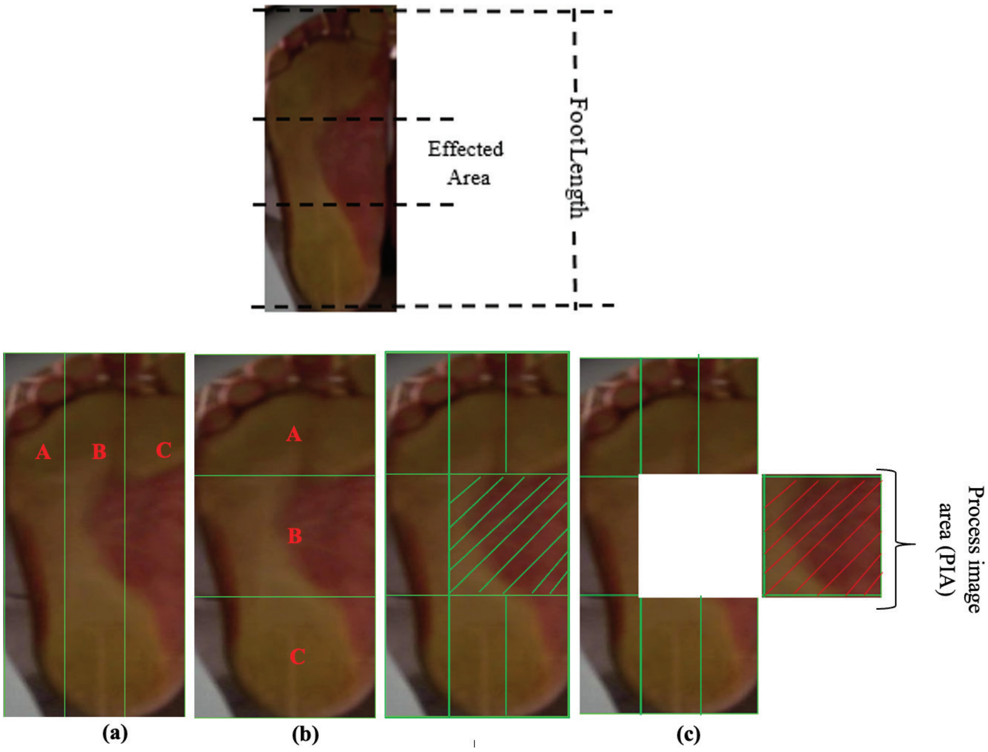


**Figure 6.** The foot arch index measurement method: (a) the demonstration of the vertical foot division, (b) the demonstration of the horizontal foot division, (c) introduces the real dataset which is stored and processed for further analyses.

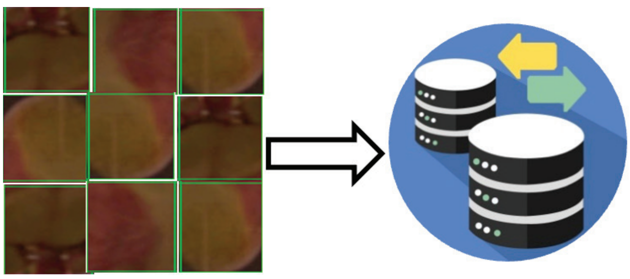

**Figure 7.** Dataset process.

the foot. In this cause, the proposed technique captures a photo by the digital camera at the bottom of the toughened glass and the foot appear mostly with two colours (red and yellow). However, in some objects, the tendons do not pull at all. In this cause, the entire bottoms of their feet of the objects touch the toughened glass and no visible arch is appeared. Thus, the feet appear mostly with yellow colour only, see Figure 7. Therefore, the proposed method calculates the percentage of red colour to the total area of PIA in order to classify the foot types based on the segmentation method. Equation 2, where the artificial intelligence is the ratio of the red colour of the PIA to the total area of PIA, measures the red colour and divides it by the total area of PIA. So, the equation calculates the normal foot when the artificial intelligence value is between 85 -36, while the foot is concave when the artificial intelligence is equal or larger than 86, and the foot is flat when the AI is equal or less than 35, which are almost the same results as those obtained by [1-3]. Figure 8 illustrates two histograms displaying the distribution of AI data for left and right feet of some example for the proposed work using the unsupervised machine learning algorithm. So the types of feet are categories as normal foot (85 <= AI <= 36), concave (AI < = 86), flat (AI < = 35).

$$\mathrm{AI} = \frac{area\ of\ PIA}{total\ area\ of\ PIA} * 100\% \quad (5)$$

## RESULTS AND DISCUSSION

This part introduces a brief description of the K-means method for image clustering with real dataset to reveal the performance of the proposed work. The proposed work is compared with other similar method. In [23], authors have improved the accuracy and reduced the time for the foot arch classification. The authors also have demonstrated their technique better than other methods. Therefore, this method is chosen as the benchmark for the comparison. Furthermore, by integrating IoT technique, our proposed method makes intelligence decision by processing and analysing data in real-time. This can enhance efficiency;

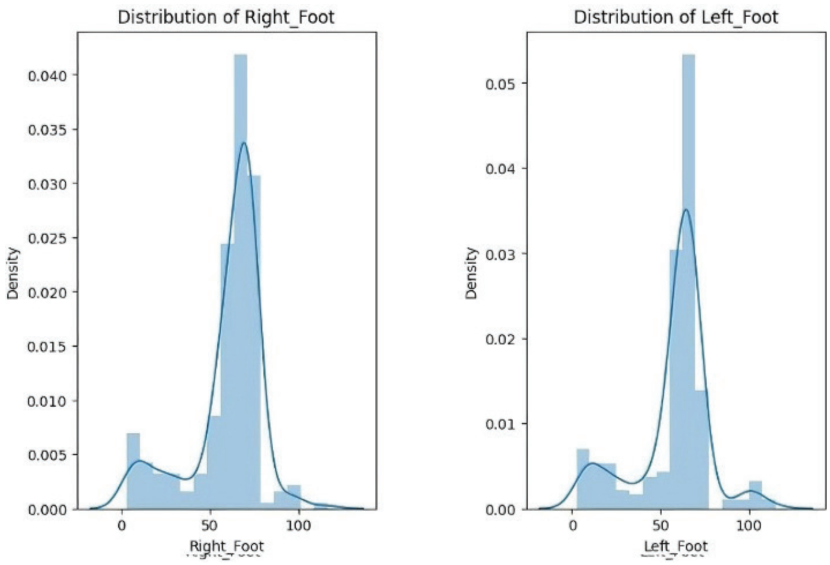


**Figure 8.** Introduces the distribution of the AI data for left and right feet.

**Table 1.** Users dataset measurements

| Subject name | Age | Right foot | Left foot | Classify right foot | Classify left foot |
|---|---|---|---|---|---|
| Ali K. Farman | Age(15-30) | 23.44 | 22.87 | Flat | Flat |
| Abd Alsattar M. Ali | Age(15-30) | 24.44 | 20.87 | Flat | Flat |
| Riyad L. Waled | Age(31-50) | 70.188 | 66.21 | Normal | Normal |
| Wadeaa K. Farhan | Age(31-50) | 70.58 | 67.21 | Normal | Normal |
| Abass B. Hameed | Age(15-30) | 90.4 | 93.2 | Concave | Concave |

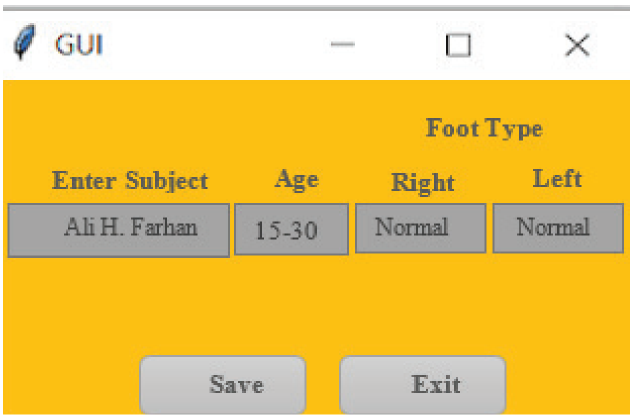


**Figure 9.** User interface results for foot type.

improve overall performance and data-driven decisions in healthcare.

The K-means technique aims to group the data into n observations in order to get the best k clusters. As we mentioned above, the data was collected from 250 participates from different ages. The proposed algorithm is performed in the python language. After the participate stands on the toughened glass, the administrator runs the code by using PyCharm platform. The application automatically scans both feet and shows the main page as explained in the Figure 9. The page contains four fields such as subject name, age, right and left feet. The name and age fields are filled manually by the administrator and others are filled automatically by foot pressure scanning using the digital camera on the bottom of the device. After this step, the administrator presses the "Save" button to insert the data into database as shown in the Table 1. This data is also transmitted and stored in the monitoring server over the internet for further analyses. After that, the software initializes the form for the next subject.

Unsupervised machine learning technique is used to analyse and clusters the dataset based on k-means algorithm. Such algorithm is used to find the hiding pattern and clustering unlabelled dataset. Figure 10 presents several scatter plots and histograms that shown to display the

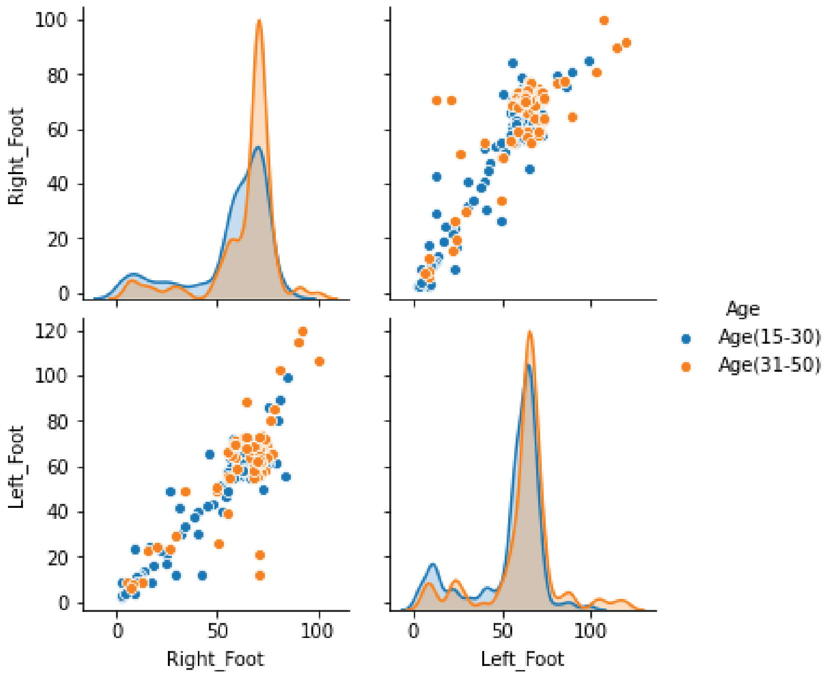


**Figure 10.** Distribution of right and left feet vs ages.

data related to foot measurements for different age clusters. The top right plot reveals two groups of data points, one for young ages group (around 15-30 years old) and another for an older ages group (around 31-50 years old). The other plot shows distributions of foot measurements, expected for the left and right feet for the different age groups.

Figure 11 presents a scatter plot that appears to display a positive correlation between the two variables right and left feet. The data points are scattered along a roughly diagonal line trending upwards from the bottom-left to the top-right of the graph, indicating that the values for one variable increase, the values for the other variable also tend to increase. As Figure 12 provides a pie chart comparing two age groups (15-30) and (31-50) respectively. The subjects with ages (15-30) shows a significantly larger portion of the total, making up nearly two-thirds of the pie chart at 63.20%. However, the subjects with ages (31-50) accounts for just over one-third of the total at 36.80%. This finding

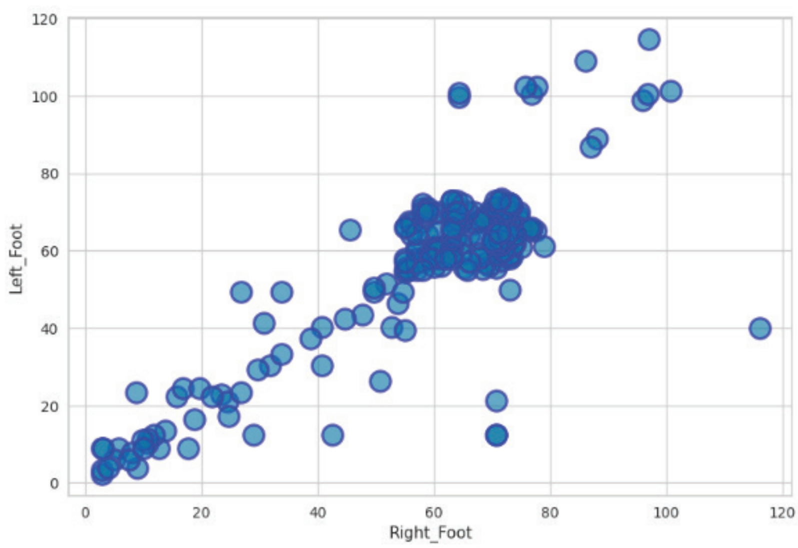


**Figure 11.** Distribution of unlabelled data.

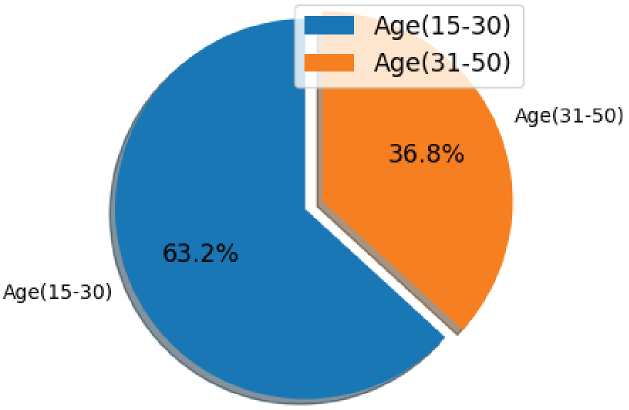


**Figure 12.** Comparing two age groups (15-30) and (31-50).

highlights that the younger age group are about 1.72 times larger than the older age group. Also, the density of scatterplots is highlighted in the Figure 13. This figure shows a density plot of the correlation between left and right feet measurements, the areas of high data concentration (density) within that scatterplot are emphasized.

The k-means technique is applied to our dataset, specifies the number of clusters (k), and then selects the optimal k data points as initial centroids. Subsequently, the method assigns the remaining data points to their closest centroid. The study uses the elbow plot method to find the optimal k and calculate the total within the sum of squares for each k. For example, Figure 14 illustrates an elbow plot and the total sum of squares distance decreases as k increases. In the figure, the k value at the location of bend (elbow joint)

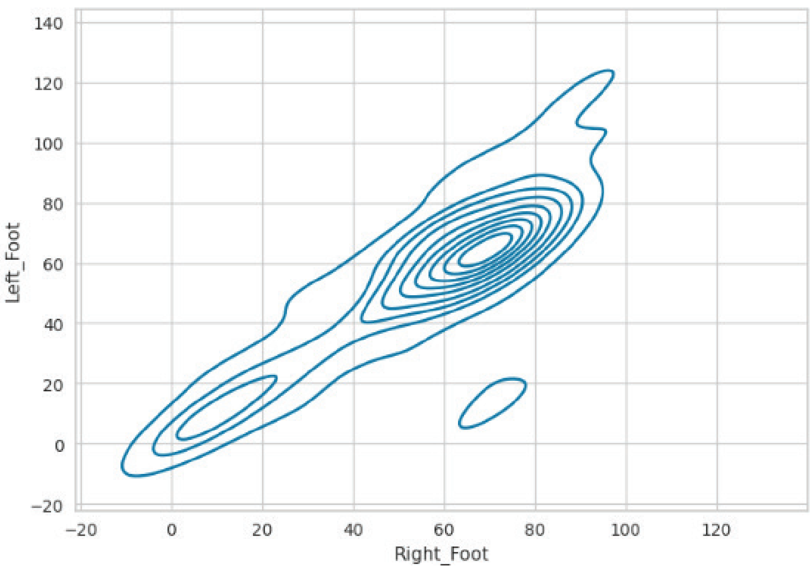


**Figure 13.** The density of scatterplots.

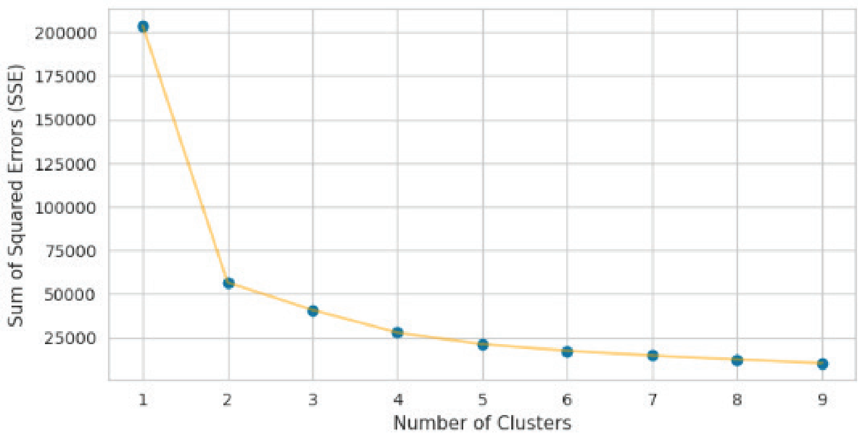


**Figure 14.** The optimal number of clusters (k).

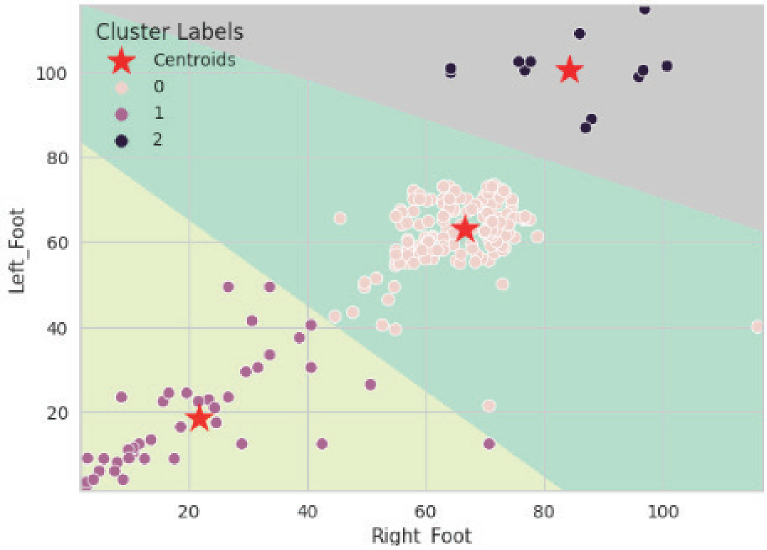


**Figure 15.** Labelled clusters.

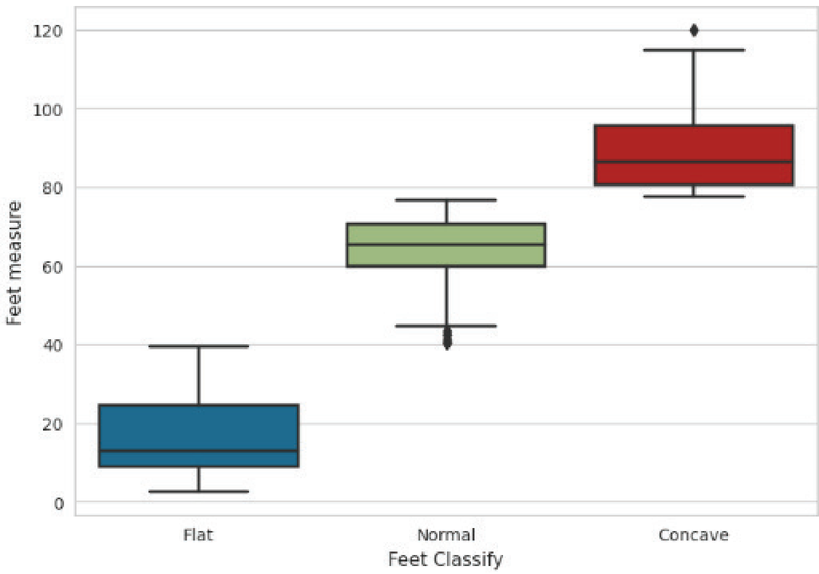


**Figure 17.** Boxplots of the distributions of numerical data for foot type measurements for 500 cases (right feet = 250, left feet = 250) as reported in Table 1. The study is categorized into three clusters normal, flat, concave feet.

is accounted as the optimal value of k. At the point of k=3, there is a significant drop in the appearance of an elbow. Thus, k=3 is considered as the optimal number of clusters.

Figure 15 introduces a scatter plot, with the right feet on the x-axis and left feet on the y-axis. From this figure, it can be seen that three clusters of feet are formed. There are several groups of coloured data points, possibly representing different clusters. These clusters are (0, 1, 2), normal, flat, concave respectively.

Interestingly, Figure 15 also observes that the normal cluster is divided into two types of clusters, namely normal and critical normal. This means that the critical normal and normal are both same type of foot. Therefore, in the following figures, both clusters are represented as normal cluster.

Figure 16 shows the proportion of different categories of foot deformities types for 250 subjects. From this figure, it is clear that the largest segment, representing the majority of subjects had normal feet with 84.2%, and 13.2% had flat feet. Only a small minority subjects had concave feet with 2.6%. However, in the present dataset above, unique cases found for a few subjects, which indicated that the subjects had a normal foot and other is concave foot. The boxplots

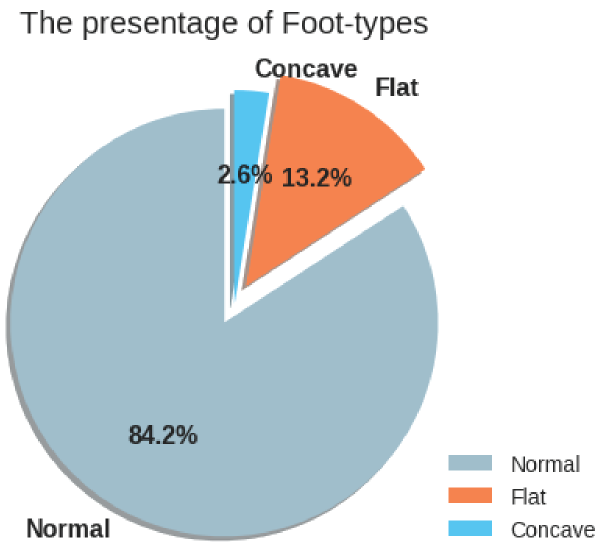


**Figure 16.** Pie chart with the percentage of foot-types.

are represented in Figure 17 and demonstrated the statistical representation of numerical data from Table 1 and divides by three groups of study. The ends of the box introduce the upper and lower quartiles, however, the second quartile (median) is signed by a line inside the box.

In order to check the performance of the classification model for the unsupervised machine learning, the confusion matrix is established. It is a table that contains two dimensions actual and predicted values. So, the dataset used was divided as follows: 20% test and 80% training model. Thus, Figure 18 indicates the results of K-means clustering algorithm, which had an overall accuracy 97.3%, while the precision and recall had 98% and 97% respectively. As illustrated in Table 2, the evaluation metrics for K-means algorithm including accuracy, precision, recall, and F1 scores for each cluster. Clearly, this work has achieved more accuracy comparing to the previous work by [22].

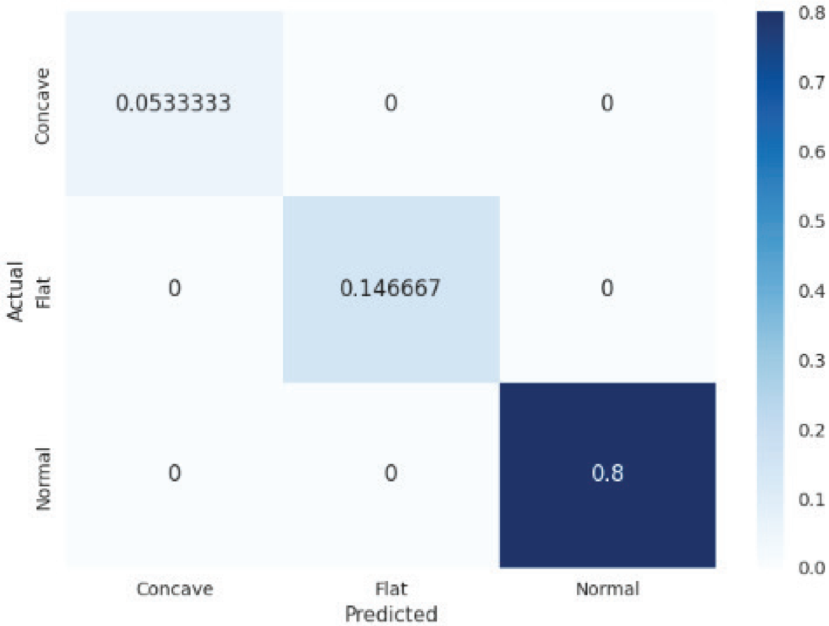


**Figure 18.** The confusion matrix for K-means clustering.

**Table 2.** Precision, F1-Score, recall, and accuracy values for the classification algorithm

| | Precision | Recall | F1-Score | Support |
|---|---|---|---|---|
| Concave | 0.98 | 0.98 | 0.98 | 5 |
| Flat | 0.98 | 0.91 | 0.99 | 15 |
| Normal | 0.97 | 0.94 | 0.98 | 80 |
| Accuracy | | | 97.3 | 200 |
| Macro avg | 0.93 | 0.95 | 0.94 | 200 |
| Weighted avg | 0.98 | 0.98 | 0.98 | 200 |

## CONCLUSION

The integration of Internet of things and artificial intelligence creates a mutually beneficial connection, so the Internet of things is a key driving factor in enabling automation systems and share data with one of the artificial intelligence methods to derive valuable insights. Therefore, the proposed scheme is involved to design Internet of things device based on artificial intelligence technology for analysing and diagnosing the foot-types deformity. The study uses segmentation method and unsupervised machine learning models to identify abnormal patterns and anomalies in the feet. The proposed study is applied to the dataset that is collected from 250 participates where they stand on the foot-types Internet of things device one-by-one and then the result classifies the foot type based on the segmentation method. Then, in turn, the Internet of things device dispatches the results of the feet to the final storage for further analysis. The experimental results introduce the superiority of unsupervised machine learning approaches in improving accuracy, sensitivity, and robustness in detecting anomalous events. The dataset is categorized into 20% test and 80% training. This study has shown that the majority of participates had 84.2%, 13.2%, and 2.6%, normal, flat-feet, and concave respectively. Thus, the results of this work reveal that the classification accuracy of the right and left feet data is as high as 97.3%, which fully reveals the superior performance of the k-means algorithm. As a result, the proposed work can have significant potential for future medical applications. Considerably more work will need to be done to develop a novel convolutional neural networks (CNNs) in order to perform pattern classification on feet data and determine whether the input individuals have foot deformity or not. More broadly, research is also required to improve accuracy by developing more robust algorithms based on various features could be beneficial.

## AUTHORSHIP CONTRIBUTIONS

Authors equally contributed to this work.

## DATA AVAILABILITY STATEMENT

The authors confirm that the data that supports the findings of this study are available within the article. Raw data that support the finding of this study are available from the corresponding author, upon reasonable request.

## CONFLICT OF INTEREST

The author declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

## ETHICS

There are no ethical issues with the publication of this manuscript.

## STATEMENT ON THE USE OF ARTIFICIAL INTELLIGENCE

Artificial intelligence was not used in the preparation of the article.

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