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Original Research Article

Advancing Foot Arch Diagnostics: A Comparison of plantar surface (PSA) index and convolution neural network (CNN) Deep Learning Models

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ABSTRACT

Introduction: Accurate assessment of foot arch morphology is crucial for diagnosing and managing various musculoskeletal conditions. The objective of the study is to test and compare the ability of the plantar surface area (PSA) index and a convolutional neural network (CNN) deep learning model to classify various foot arches normal arched foot (NAF), (FAF) and high arched foot (HAF) from plantar scan images.

Methodology: This is a comparative study in which a total of 896 male participants, aged 25–45, were randomly selected and evaluated for foot arch classification into three categories: NAF, FAF, and HAF. 360 images were taken to train, test and validate the CNN model. The PSA index method involved traditional footprint analysis using a self-designed foot scanner, while the CNN model was trained on a dataset of foot images to automate classification.

Results: Descriptive statistics was used to tabulate the demographics, and the performance of CNN and PSA was done which showed 100% sensitivity, specificity, positive predictive value (PPV), and negative predictive value (NPV); both approaches were able to classify all 130 instances in each category with flawless precision. For both approaches, there were no false positives (FP) or false negatives (FN) noted.

Conclusion: Future studies should develop hybrid models that harmonize anatomical precision and biomechanical accuracy with CNN efficiency paving the way to personalized medicine and real-time diagnostics. If these challenges are met, researchers would be able to fully leverage this interdisciplinary approach to affect both clinical practice and biomechanical work.

KEY WORDS: Foot arch classification, PSA index, Convolutional Neural Network, Deep learning, Biomechanics, Artificial intelligence.

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INTRODUCTION

Precise categorization of foot arch types is an integral part of foot condition assessment and development of effective interventions in the clinical and athletic domains [1]. The foot's arches are categorized structurally as Lateral longitudinal arch (LLA), Medial longitudinal arch (MLA), and Transverse arch (TA) [2].

During weight bearing, the MLA functions as a spring and is higher than the LLA [3]. In FAF, also known as pesplanus, the plantar surface of the foot nearly touches the ground, and the MLA height is either entirely or partially flat [4]. Exaggerated MLA height is referred to as high arch foot or pes cavus [5]. Accurate diagnostics instrument is required due to biomechanical differences between normal arched foot (NAF), flat arched foot (FAF) and high arched foot (HAF) affect the posture, leg tonus, as well as injury risk during the locomotion process [6].

Traditional classification methods like the Chippaux smirak index, Arch index, Staheli index and plantar Surface Area (PSA) Index are still widely used due to their simplicity and effectiveness for categorizing foot arches [7, 8]. However, the scalability of these manual or semi-automated approaches is hampered by labour intensity, the necessity for precise manual measurements, and variability between observers [9].

In comparison, automation of medical image analysis has remained a very actively researched approach, owing to advances in artificial intelligence, particularly Convolutional Neural Networks (CNNs) [10]. CNNs are successfully applied to many areas within medical imaging, including orthopaedics and podiatry, yet their potential in foot arch classification has been underutilized [11]. Deep learning models is a part of CNN which have the potential to be used to create automated podiatry evaluations [12]. Potluri S. (2019) showed the potential of CNNs in analyzing plantar pressure distributions and gait patterns, achieving results comparable to experienced clinicians [13]. Foot print indices are simple, inexpensive but it is time-consuming, therefore these foot print indices and PSA indices has to be automated to reduce the time as well as to improve the accuracy [14]. The above literature showed that several studies have validated that classic measurements, such as the PSA Index and Staheli Index, are valid and reliable in classifying the types of foot arches but time-consuming. There is a research gap in the footprint indices in association with CNN-based methods for the image-based classification of foot arches. Hence, there is a clear lack of research in this domain. To fill this research gap, the present study aims to test and compare the ability of the PSA Index and a CNN deep learning model to classify various foot arches (normal, flat, and high) from plantar scan images.

MATERIALS AND METHODS

In this comparison study, 896 male participants between the ages of 25 and 45 were randomly selected. Participants with dislocation, fractures, limb length disparities in the lower limb, any diseases of the bone, muscle or connective tissue problems, and neurological abnormalities such as poliomyelitis were excluded. The Sri Ramachandra University in Chennai, Tamil Nadu, has an Institutional Ethical Committee (IEC), REF: (IEC – NI/14/DEC/44/93), which approved the study's conduct. Participants were chosen, recruited, and submitted to foot arch after being fully told about the goal of the study.

a. Evaluation of the foot's arches: The present investigation used a self-designed foot scanner that was constructed using wood, toughened glass, and a document scanning machine. The apparatus can support a weight of up to 200 kg when an individual stands on the equipment depicted in Figure 1. A towel was used to carefully dry the participant's foot after it had been cleaned with mild soapy water. A series of familiarization trials were conducted before the digital plantar scan images were obtained. Each participant was told to stand straight, looking forward, on the podoscopic apparatus. The computer was updated with the plantar surface photos. Calibration markers were placed in two locations that were separated by a predefined distance, and the actual distance in centimetres was entered into AutoCAD to calibrate the images. The participants were directed to maintain an upright posture and gaze ahead through the self-constructed podoscope device; after many acclimatization trials, the superior images generated by the podoscope were transmitted and archived on the computer.

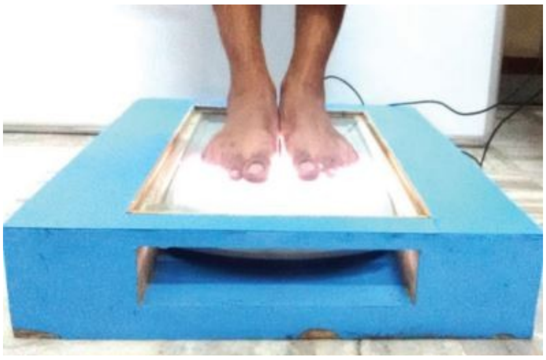

Fig. 1: Self designed foot scanner.

Method I

i) The Plantar surface area (PSA) index was used to assess the images with AutoCAD software. Based on PSA the arches of the foot was categorised into normal arch (NAF), flat arched foot (FAF) and high arched foot (HAF) as FAF grade 3, FAF grade 2, FAF grade 1, HAF grade 3, HAF grade 2, and HAF grade 1 PSA consists of 3 measurements: i) total plantar surface area (TPSA), and the whole plantar area. ii) Plantar surface contact area (PSCA) connects the forefoot, midfoot, and hindfoot, primarily in contact with the ground. iii) Plantar surface non contact area (PSNCA) located at the concavity of the (MLA), which is devoid of contact with the ground as shown in figure 2. a, b, c.

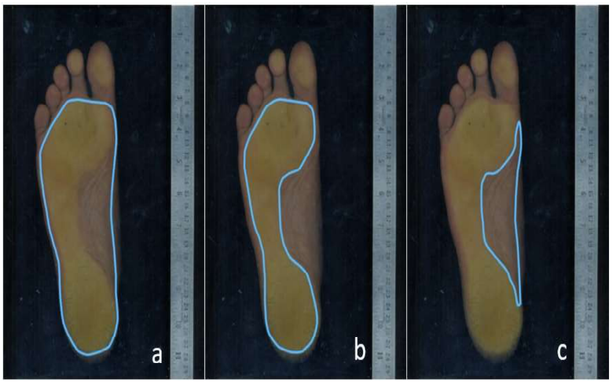

Fig. 2: a. total plantar surface area (TPSA),
b. Plantar surface contact area (PSCA),
c. Plantar surface non contact area (PSNCA)

ii) Flat arch foot (FAF): The flat arch foot was classified into three groups according to the PSA index. The MLA was totally deflated, the dominant medial protuberance was apparent, the rear foot width decreased, the PSCA's contact zone was 100%, and the PSNA was 0% in FAF Grade 3, as shown in Fig. 2 (5–7). The MLA disappears, the midfoot's width increases to the forefoot width in FAF Grade 2, the PSCA ranges from 91% to 99%, and the PSNCA ranges from 0% to 10%. The midfoot's width was expanded, and the conventional MLA structure was changed in FAF Grade 1. The midfoot now supports at least one-third of the entire foot region, and the plantar surface contact area (PSCA) is between 80% and 90%, as shown in Figure 3. a, b, c.

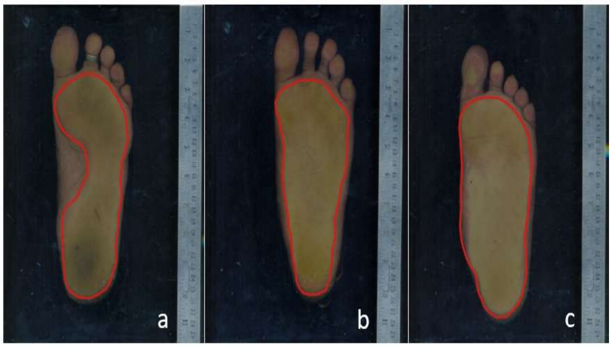

Fig. 3: a. FAF grade 1, b. FAF grade 2, c. FAF grade 3 (FAF – Flat arched foot)

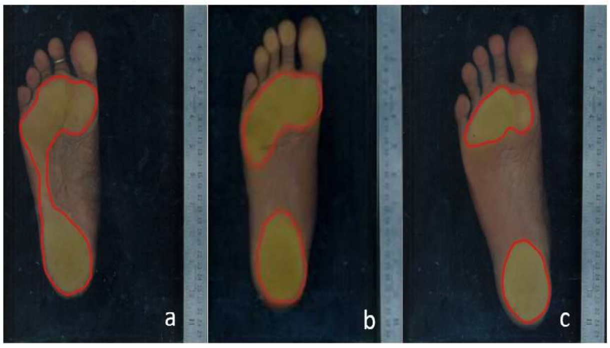

Fig. 4: a. HAF grade 1, b. HAF grade 2, c. HAF grade 3 (HAF – High arched foot)

iii) High-arched foot (HAF): The PSA index was used to identify three distinct categories for the high-arch foot. In HAF Grade 3: The entire contact area of the plantar surface to the floor is reduced, as seen by the PSCA, which is only roughly 21%–40% in Fig. 2 (8–10). The MLA's structure was disrupted in HAF Grade 2, and there was no midfoot contact with the ground at all. The heel and metatarsal area are the main points of contact with the floor, and the

PSCA ranged from 41% to 50%. The PSCA was between 51% and 60% in HAF Grade 1, where the midfoot width was reduced, and the medial longitudinal arch's concavity increased, as shown in Figure 4. a, b, c.

Method II

Dataset organization: To automatically identify various arches from the saved plantar scan images (dataset) obtained from the scanner, a Convolutional Neural Network (CNN) was installed into place. Three primary folders were created from the dataset: "training_dataset," "validation_dataset," and "test_dataset." To ensure that the data is well-structured and prepared for use in training a Convolutional Neural Network (CNN), each of these folders has subfolders for Normal arched foot, Flat arched foot, and High arched foot. With its large number of photos, this dataset is specifically made to train a CNN to categorize images of NAF, FAF, and HAF. This enables the model to learn and generalize efficiently. Every set of data has a distinct function throughout the training and assessment of the model.

i) The training dataset: Normal arched foot 100 images, flat arched foot 100 images, and high arched foot 100 images make up the majority of the dataset. Within the main "training_set" folder, there are three subfolders containing a total of 300 images: one for NAF, one for FAF, and one for HAF. This high quantity of labeled photos guarantees that the model has enough information to identify the characteristics that set the three classes apart. In order to reduce classification mistakes, the CNN repeatedly iterates over these images during training.

ii) Validation Set: To make sure that the model's performance is reviewed using more than just the training data, a validation set was constructed. There are 60 photos in all in this set: 20 NAF, 20 FAF, and 20 HAF photos. These 60 photos were originally included in the test, but they were later transferred to a different "validation_set" folder where they were used to adjust model hyperparameters and keep an eye out for overfitting. The validation set helps to improve the model and prevent overfitting by offering an objective assessment of the model throughout the training stage.

iii) Test Set: Following training and validation, the model's performance is assessed using this test set. A total of 30 photographs make up this set: 10 NAF, 10 FAF, and 10 HAF photos. Within the "test_dataset" folder, these pictures were arranged into two subfolders. A final evaluation of the model's ability to generalize to new, untested data was provided by the test set, which also ensured that the model's predictions were reliable and sound.

Setting up the environment, importing the necessary libraries, and preparing the dataset: The Google Cloud AI Platform was installed via pip install google-cloud-ai platform. Using pip install TensorFlow, Tensor Flow was installed. This robust deep-learning library is essential for neural network construction and training. To plot and visualize the data, Matplotlib was used. Confusion matrices were created using Scikit-Learn. The numerical operations were imported and arrays were handled using NumPy. To handle warnings and perform file operations, utility libraries like OS, Random, Glob, Shutil, Itertools, and Warnings were imported.

Developing, Assembling, and Training a CNN Model

a. A CNN for the foot's arches was developed using a sequential model, which enables the stacking of image layers in a straight line. **i) Convolutional Layers:** To extract features from the images, convolutional layers were created using Rectified Linear Unit activation (ReLU) functions. **ii) Max-Pooling Layers:** These layers served to downsample the input while preserving significant features by reducing the spatial dimensions. **iii) Flattening:** The output was made into a one-dimensional array.

b. Gathering the foot model's arches: i) Optimizer: The Adam optimizer was chosen due to its effectiveness and capacity for flexible learning rate, which facilitates quicker convergence. (ii) Loss Function: Due to its suitability for multi-class classification problems, categorical cross-entropy was selected as the loss function.

Training the Model

i) Data Feeding: To optimize its parameters according to the designated optimizer and loss function, the CNN architecture was fed data from the training and validation datasets. **ii) Epochs:** The model iterated over the full training dataset ten times after setting the epochs to that number. **iii) Training Process:** The model made predictions on the training data during each epoch, and it changed its parameters based on the calculated loss during the backward pass.

Making Predictions: Following the model's training on the validation and training datasets.

i) Model Application: The test dataset, which includes unseen foot images that the model has not seen during training, is used to apply the model.

ii) Making the Predictions: For every image in the test dataset, predictions were made using the prediction approach. Usually, these predictions are made up of class probabilities, which each indicate the probability that the foot picture belongs to a specific class.

Comparison of PSA index and CNN model output

Method 1 (based on the PSA index) and Method 2 (based on the Convoluted Neural Network (CNN) classification model) were compared.

RESULTS

Descriptive statistics was used to tabulate the demographic data of the participants, as in table 1. Reference values to classify the NAF, FAF and HAF are tabulated in Table 2. Distribution of NAF, FAF and HAF are tabulated based on the severity using the PSA index in Table 3. Selection, training, validating and testing CNN model in table 4. The performance of CNN in classifying the different foot arch types (normal, flat, and high) and compared with PSA index in table 5. With 100% sensitivity, specificity, positive predictive value (PPV), and negative predictive value (NPV), both approaches were able to classify all 130 instances in each category with flawless precision. For both approaches, there were no false positives (FP) or false negatives (FN) noted in table 5.

Table 1: General characteristics of the subjects

Gender	Age Mean(SD)	Height Mean(SD)	Weight Mean(SD)
Men	33.4 ± 8.9	177±3.4	77.4±9.8

Table 2: Reference values for different types of arches of foot.

Normal arch foot (NAF)	61% - 79%
FAF	80% - 100%
FAF Grade I	80% - 90%
FAF Grade II	91% - 99%
FAF Grade III	100% with protrusion
HAF	<61%
HAF Grade I	51% - 60%
HAF Grade II	41% - 50%
HAF Grade III	21% - 40%

Table 3: Distribution of different types of arches of foot

PSA Index		Grades					
		F 1	F 2	F 3	H 1	H 2	H 3
Normal arched foot	562	0	0	0	0	0	0
Flat arched foot	186	82	44	60	0	0	0
High arched foot	148	0	0	0	64	34	50
Total	896	82	44	60	64	34	50

Table 4: Selection of different types of arches of foot images to train the CNN model.

Types of arches	PSA Index	CNN		
		Training dataset	Validation dataset	Test dataset
Normal arched foot	130	100	20	10
Flat arched foot	130	100	20	10
High arched foot	130	100	20	10

Table 5: Comparison between the PSA index and CNN model in identifying different types of arches of foot.

Metrics	PSA Index	CNN
Sensitivity (%)	100	100
Specificity (%)	100	100
Positive Predictive Value (%)	100	100
Negative Predictive Value (%)	100	100
False Positives (FP)	0	0
False Negatives (FN)	0	0

DISCUSSION

The present study investigated the arches of the feet of 896 male participants by obtaining the plantar scanned images, and the comparison was made between the PSA index and the CNN model tables 3 and 4. The study showed that the CNN automated model was highly effective in identifying the different types of arches with more accuracy and in less time when compared with PSA index tables 4 and 5.

a. Contributions of Anatomy and Biomechanics in CNN Analysis: The convergence of anatomical, biomechanical, and convolutional neural network (CNN) approaches has revolutionized our understanding of human movement, pathology, and rehabilitation [15]. While existing research has investigated the three domains in isolation and in combination, they provide valuable insights into their respective advantages and limitations. This discussion compares and contrasts these contributions relative to the existing literature, emphasizing how they interact while also indicating areas for future work.

b. Anatomical Comparisons and Advances: Anatomical studies, by definition, are fundamental to musculoskeletal understanding, specifically with respect to the joint, soft tissue interactions, etc. Conventional anatomical research depends on cadaver observations, histology, and human interpretation of images [16]. For instance, Miller et al. (2016) [17] proved the viable use of magnetic resonance imaging(MRI) for the visualization of soft tissues, including cartilage and ligaments, with never-before-seen resolution in comparison to prior modalities such as X-rays. While these conventional methods were effective, they typically entailed considerable manual labour, restricting their scalability and reproducibility. Similarly, the present study has developed a model which can automatically identify the different types of arches of the foot with more accuracy and in less time when compared with the conventional method.

There have been more recent studies which utilize advanced imaging techniques such as high-advanced resolution-computed tomography (CT) and 3D ultrasound to visualize microanatomic structures. For instance, Zhang et al. (2020) [18], temple 3D imaging has been used to generate maps of complex joint geometries, which also emphasizes variability in anatomical structures within populations. These approaches to processing and analysing large datasets have yet to face challenges. Convolutional neural networks, or CNNs, have been shown to be the most effective tools in addressing these problems. And, for instance, Ronneberger et al. (2015)[19] proposed the U-Net architecture, which has become a widely-used approach for biomedical image segmentation. This method allows for the automatic recognition of anatomical landmarks and, therefore, significantly decreases the time and work involved in textual evaluation. Similarly, the present study has developed a model which can automatically identify the different types of arches of the foot with more accuracy and in less time when compared with the conventional method in tables 4 and 5; thus, we agree with Zhang et al. and Ronneberger et al.

Integrating CNNs with anatomical analysis has been more accurate and efficient than traditional approaches. Litjens et al. (2017) [12], found in their review of >300 applications of deep learning in the medical field that CNNs performed better than other techniques at segmenting and classifying anatomical structures. If not sufficiently represented in training data, anatomical variation due to factors such as age, sex, or underlying pathology may contribute to biases. The present study trained the CNN model with 100 images in the training dataset in each category; therefore, the model got the ability to identify the NAF, FAF and HAF with high accuracy.

c. Anatomical Investigations its benefits and limitations: When it came to the effect of forces and motions on anatomical structures, biomechanics has played a major role. In the early days of biomechanical research, investigation of human movement occurred in controlled laboratory environments, using devices like motion capture systems and force plates. Venkata Sushma et al. (2018) [20] performed an FEA analysis of stress distributions in the knee joint and investigated potential injury mechanisms and prosthetic designs. Although FEA provides rich biomechanical information, it demands high computational power and a precise anatomical model, which is frequently based on imaging data. In the present study, a total number of 360 images were used to train, test and identify the images using the CNN model; this enabled good accuracy in predicting the different types of feet; thus, we agreed with Venkata Sushma et al.

d. The Efficiency of CNNs in identifying the arches of the foot: Anatomical and biomechanical research has been enhanced with the rise of convolutional neural networks in data analysis. Until recently, analysis of imaging data relied on difficult manual segmentation and feature extraction, which were slow and prone to human error. CNN, on the other hand, automates these processes and allows us to analyze large datasets with great accuracy. Esteva et al. (2017) [21], showed that CNNs could match dermatologists in the classification of skin lesions, opening the potential of deep learning for analysis in a medical context. A study by Balakrishnan et al. (2022) [22] implemented CNNs to predict muscle forces during dynamic activities, with results close to those obtained by EMG. This method not only facilitates data collection but also provides a novel means of non-invasive biomechanical characterization. Johnson et al. have also used CNNs to predict injury risk through gait analysis. The present proves that high-quality annotated datasets limit the use of CNNs, demonstrating a need for cooperation between anatomists, biomechanists, and computer scientists to create robust models.

CONCLUSION

Overall, the use of anatomical, biomechanical, and CNN approaches in tandem has revolutionized our understanding of human movement and pathology to date. Though anatomists have powered studies through increasingly advanced imaging techniques, they are now complemented by CNN-based automation to develop a methodology to deliver faster and more reliable analyses. The biomechanical investigation has also developed, with CNNs providing novel techniques for predicting kinematics and internal forces. However, dataset dependency, anatomical variability, and model generalizability point to the necessity for more research. Future studies should develop hybrid models that harmonize anatomical precision and biomechanical accuracy with CNN efficiency paving the way to personalized medicine and real-time diagnostics. If these challenges are met, researchers would be able to fully leverage this interdisciplinary approach to affect both clinical practice and biomechanical work.

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Author Contributions

Haripriya M: Concept and Design of the Study,
Vijayakumar S: Results interpretation and analysis
Vijayakumar K: Literature review, Manuscript preparation and drafting.

Conflicts of Interests: None

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