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PESNET: A CNN FRAMEWORK TO PREDICT THE GENDER OF HUMANS USING BARE FOOTPRINTS

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Abstract

In forensic science, one of the common applications of personal identification occurs in cases involving unidentified human remains. This work proposes PesNet, a gender prediction framework from bare footprints using a novel convolutional neural network (CNN). In this study, a dataset of 1,000 human barefoot impressions, evenly split between male and female sample impressions, collected from the different administrative division of Haryana, India, was exploited to visualize and analyze the shape and sizes by utilizing deep learning approaches. PesNet architecture in this article uses higher order preprocessing methods such as Gaussian filtering and grayscale conversion to improve image quality and minimizes environmental noise. PesNet, deployed with a pre-trained model, prevailed over conventional methods and established models to achieve a stunning gender classification accuracy of 96% are the findings of our study. This research not only highlights the potential of deep learning in forensic applications but also addresses challenges such as class imbalance and the need for reliable identification techniques in criminal investigations.

Index Terms:
Forensic science, Deep CNN, PesNet, Bare footprints, Gender, Personal Identification.

I. INTRODUCTION

Forensic science is an essential multi-disciplinary science which helps tackle crime investigation and litigations. It is the use of complex scientific principles and techniques to analyze evidence, solve crimes, and bring facts to a court of law [1]. Personal identification is an essential component of forensic science, especially in the case of unidentified human remains and unknown individuals attempting to conceal their identity [2].

Anthropometry and the different molecular techniques like DNA, odontology, fingerprint, and biometrics, along with lip prints, are the major methodologies in the personal identification which are the five essential parts of forensic anthropology ([3]. Such methods assist in extracting important characteristics like age, sex, stature, and ethnicity, all of which play a vital role in establishing the identity of an individual [2]. This combination of different forensic techniques allows for comprehensive and reliable identification results to be provided to assist in the resolution of missing persons cases and support the justice system [4].

Footprints, the foot, bare footprints are defined very differently in the literature and are important to understand the context of forensic science. 'Footprint' can either refer to two-dimensional or three-dimensional shoe marks [5], while 'foot' signifies the entire anatomical structure including skin [6]. The term 'bare footprints', is defined in forensic podiatry as patent prints produced by the friction peak skin of the undersole, which may be developed using colour matter of contrasting colour against a contrasting background [7,12]. Their wide variety of bare footprints can also be used as unique IDs, similar to fingerprints; every individual's configuration of ridges is different [8]. They are significant at crime scenes, particularly in cases especially in sexual assault or homicide cases, where they may contain important evidence that linking a perpetrator to a location [9,10]. Individual characteristics like shape, size and orientation also can be gleaned from the analysis of footprints, helping to identify the individual 3 and providing information on stature, weight, sex and movement [11,12].Previous studies have shown that some characteristics of bare footprints can reveal sexual dimorphism and help to determine the sex of the person [13,14]. Overall, the forensic examination of bare footprints is a valuable tool for establishing the presence of individuals at crime scenes and can significantly influence investigative outcomes [15,16,17].
According to the current literature, involves seven methods for the evaluation of bare footprints. The seven techniques can be categorized in two groups. Group 1 includes methods for individual typography characterization for ID, and group 2 includes methods for classifying foot typologies (for criteria of riding selection) or diagnosing foot pathologies [18]. Table 1.1 shows the two groups, which parameters are measured and how the method can be applied, purpose, accuracy, reliability, identifiable characteristics.

TABLE I: Illustration of bare footprints evaluation methods, type of parameter measure, and the application.

Method Name	**Type of Mea-surement**	**Purpose**	**Notable Characteris-tics**	**Accuracy (%)**	**Reliability (%)**	**Identifiable Char-acteristics**
Gunn Method	Linear measure-ments	Identification	Constructs lines from heel to toes; widely used but originally anecdotal.	90%	90%	Age, sex, weight
Reel Method	Linear and angu-lar measurements	Identification	Incorporates additional measurements; shown to have high reliability.	95%	95%	Age, sex, weight
Robbins Method	Visual anthropo-logical measure-	Identification	Combines diagonal and parallel axis	Not applicable	Not applicable	Not applicable

	ments		methods; discredited due to controversy.			
Rossi's Podometrics	Linear measurements	Foot type classification	Uses a grid of longitudinal and transverse lines; primarily for clinical use.	Not specifically validated for forensic use	Not applicable	Foot type, potential pathologies
Optical Centre Method	Linear measurements	Identification	Assigns an optical center to morphological features; developed by RCMP.	85% (estimated)	Lower reliability compared to Gunn and Reel methods	Age, sex, weight
Overlay Method	Morphological outline tracing	Identification and foot type	Traces known footprint outlines over questioned prints for visual comparison.	Subjective; reliability varies	Varies widely	Age, sex, weight
Geometric Morpho-metric Method	Morphological analysis	Foot type classification	Uses a comprehensive set of landmarks to an-alyze footprint shape.	Not specifically validated for forensic use	Not applicable	Foot type, potential pathologies

Gunn method and Reel method, as two major individualization methods based on footprints characterization, use linear measurements from footprints to identify the individuals; among these methods, Reel method is characterized by the highest reliability and accuracy that is suitable for forensic investigations. Moreover, the Rossi's Podometric, and the Robbins method are linear measurement methods traditionally used and currently the Robbins method is less favored due to debates regarding its validity. [19].The Optical Centre method also uses linear measurements, joining the optical centres of the heel and the toes. H ow e ve r , this method focuses on morphological analysis, enabling the identification of the shape and structure of the footprint without necessarily measuring it [20].

Footprint analysis methods, while useful in forensic investigations, have several limitations. These include variability in footprint quality due to environmental factors, subjectivity in expert analysis leading to potential biases, and measurement errors associated with various techniques. Additionally, many methods require complete prints for accurate analysis, which can be challenging with partial prints. The statistical validity of some methods is questionable, and footprints often exhibit class characteristics rather than unique individual traits, complicating individualization. Technological limitations and the lack of standardized protocols further hinder the reliability of these methods[19]. Most of the footprint analysis will be done using the old traditional methods, which are usually very time-consuming and challenging with lots of demerits as mentioned (19,20].

The deep CNN network is used in the proposed study to detect the footprints. Convolutional neural networks have recently overcome the demerits of traditional methods. In 2019, A CNN model was proposed by a team of researchers to identify humans from footprints. They collected a dataset of 30 individuals and achieved an accuracy of 98.52% [21].

Another study was done to identify age, gender, and weight based on human tongue images. In this, the deep CNN models were trained on a large sample size of 10,590 individuals and achieved an accuracy of 80% [22].

Another study was done to identify age and gender and created an automated age and gender identification system based on orthopantomograms (OPGs) of teeth. It used a dataset of 1,142

digital X-rays and obtained 96% accuracy for gender prediction and 97% for age prediction [23].Footprint identification can be framed as a pattern recognition problem. Other disciplines have also undergone similar study, one example is the use of deep learning to extract characteristics from plant leaf. Moreover, in the medical field like in distinguishing between different Disease patterns of MRIs and CT scans [24]. Results show an ability of deep learning classification to identify individuals from bare footprints. We can approach this problem as a classification problem which is concerned with a sub-categories of gender. The impetus of the challenge was motivated by the state-of-the-art pretrained models already existing such as that which were found to give rise to the training of the colored images in our dataset, classifying them with Transfer Learning. In this paper, we introduce a novel approach that challenges both large pretrained architectures and traditional methods. Our state-of-the-art Deep CNN architecture, PesNet, utilizes greyscale and Gaussian- filtered images as input, enabling highly accurate gender prediction. This pre- processing enhances the removal of environmental noise from each image, allowing our model to outperform pretrained architectures. Additionally, our proposed method addresses the class imbalance issue, a key limitation identified in many pretrained models.

The specific contributions of this work include:

- If you need to extract minute detail the Pesnet architecture, then we recommend using

Pesnetlayer. Pesnetlayer is capable of reducing environmental noise and extracting edge from the side.

- These advantages demonstrate the state-of-the-art lightweight architecture of Pesnet,which is capable of reducing the computational challenge of the training procedure.

The remaining research paper is organized in the following structure: The data is described in Section II, the study methodology and the purposed architecture are described in Section III, the experiment findings are shown in Section IV, and the results, their application, and their future scope are discussed in Section V.

TABLE II: Filters utilized in each convolutional layer across the PesNetLayers.

S/N	PesNet-Layer	Convolution-4	Convolution-2	Convolution-3	Convolution-1
1	PesNetLayer-A	128	64	64	32
2	PesNetLayer-C	128	128	256	256
3	PesNetLayer-B	128	128	512	256

II. THE PROPOSED METHODOLOGY

A. EXPLANATION OF PESNETLAYER

As shown in Fig. 1, the Pesnet has made use of three different types of PesnetLayer: PesnetLayer-A, PesnetLayer-B, and PesnetLayer-C. Each PesnetLayer comprises of three batch normalization layers, one max pooling layer, and four convolutions (Conv-1, Conv-2, Conv-3, and Conv-4).

Table 3 shows that the convolution layers in each PesnetLayer employ various filter sizes. As seen in Table 3, the quantity of local and global characteristics to be recovered from bare footprints is determined by the number of filters in each PesnetLayer. PesnetLayer-A is used to extract the bare footprint's minute details. While PesnetLayer-B and PesnetLayer-C extract the bare footprint's global properties,

Using convolution, batch normalization and max-pooling on each PesnetLayer, helps learn larger (size difference, internal attributes of class)- and smaller features (edges of footprints, their shape, size). Using batch normalization also prevents the exploding and vanishing gradient problem.

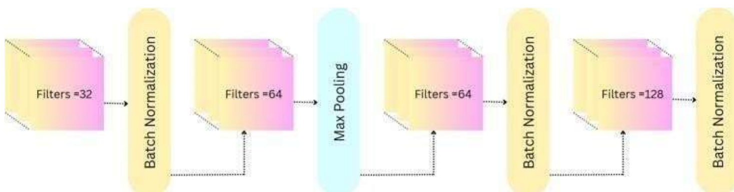
Pesnet uses a filter size of 3 × 3. for each convolution layer to extract finer details. Table 4 is the performance of Pesnet with different filter sizes. We can note that Pesnet accuracy drops with larger filters. Pesnet works well with a filter size of 3 × 3. and grayscale input images. Thus, the proposed PesnetLayer employs a filter size of 3 × 3.

B. OVERVIEW OF PESNET

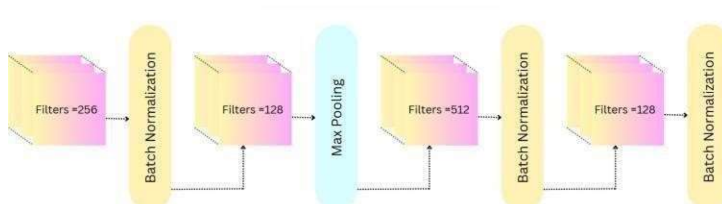
Pesnet draws inspiration from spatial exploit models like LeNet and AlexNet as well as depth-based CNNs like ResNet and Inception. Pesnet aims to develop a new model that can identify key features and evaluate the edges of a human bare foot-print. They can be used for gender differentiation. Since they can extract features from human footprints, PesnetLayers are used to build Pesnet.

TABLE III: PesnetLayer's performance with various filters.

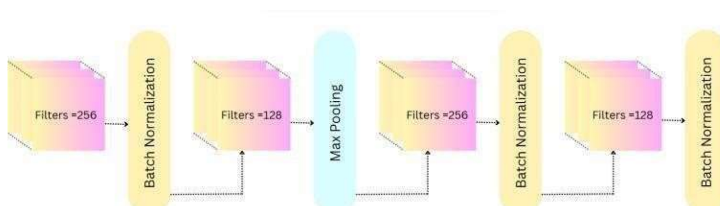
SN	Filter Size	Accuracy
1	7 × 7	71%
2	5 × 5	83%
3	3 × 3	96%



(a) PesNet Layer A



(b) PesNet Layer B



(c) PesNet Layer C

Fig. 1: The block diagram of the PesNet Layers.

As represented in Fig. 1, the proposed Pesnet is made up of three PesnetLayers with input and output layers (PesnetLayer-A, PesnetLayer-B, and PesnetLayer-C) The first input layer of the Pesnet receives an input image with a 224 × 224 resolution. three different kinds of PesnetLayers process the input image. Pesnet used ReLU as an activation function to underline the model's non-linearity.

TABLE IV: Performance of the Pesnet with different Epoches.

S	Number of Epoch Cycle	Accuracy
1	20	78%
2	50	96%
3	100	91%

Each layer's filter count has been progressively increased. which is shown in Table 3. These different filter sizes made it easier to understand more global feature levels. Then, Smaller

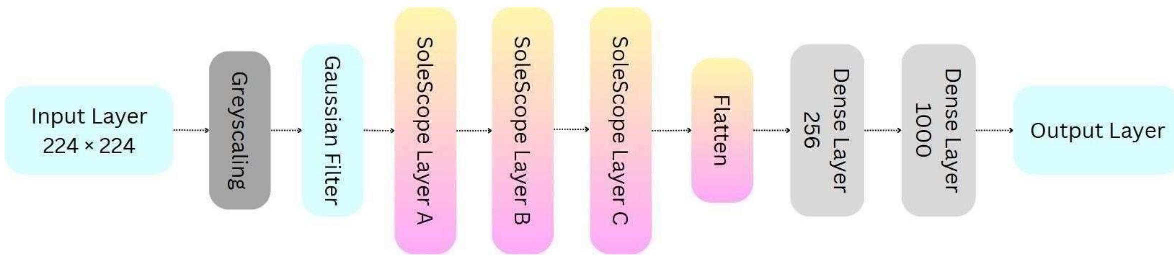


Fig. 2: Detailed architecture of the PesNet.

filters were used to collect local information while larger filters were used to extract size and shape of the foot. Using two such dense layers with fewer neurons has proven to work well. The three different Pesnetlayer types were combined to help detect edge cases.
Next, Table 4 shows the Pesnet performance with different Epoch Cycle. It is noticeable that the Pesnet performs at its peak at 50 epoch . and the performance decreases with increased number of epoch cycle (Overfitting) and decreases with decrease number of epoch cycle as well (Underfitting).. Therefore, in order to achieve the best results, the proposed Pesnet used the 50 epoch.

III. EXPLANATION OF THE EXPERIMENTAL DATA

Human barefoot print images have been collected from five administrative divisions of Haryana India namely(Faridabad, ,Gurugram Hisar, Karnal, Rohtak)The consent forms duly signed by the all participants was taken. The location of the sample collection and the number of male and female samples collected from each division of Haryana are listed in Table 6. These images have been scanned using a Epson flatbed scanner. The images are scanned at 300 DPI and saved the scanned image in laptop to create a dataset. All the images have been scanned with same process. Total 1000 different human barefoot prints images have been collected from these 5 admirative divisions of Haryana out of which 500 footprint images are of female and 500 are of male. The minimum and the maximum age of the participants are 18 and 60 respectively. So, the tagged photos are matched against the original footprint image to catch any mistakes in annotations. Then the images go through more pre-processing. which provides feedback to the architecture we are envisioning.

A. Data Analysis

The images are preprocessed along torchvision, python, and PIL libraries. Six different highly developed architectures (NasNet, VGG19, VGG16, InceptionResnetV2, InceptionV3, ResNet50) are applied on footprint images in TensorFlow.

TABLE V: An overview of the suggested dataset for barefoot prints

Gender	**Samples per g e n d e r**	**Resolutions (DPI)**	**Types of Images**

Male	500	300	RGB
Female	500	300	RGB

Fig. 3: The Foot prints of Female

Fig. 4: The Foot prints of Male

TABLE VI: Showing the data collection locations in haryana, India.

Area	**Latitude**	**Longitude**	**Male**	**Female**
Faridabad	28.387218	77.298655	100	100
Gurugram	28.441302	77.020682	100	100
Hisar	29.599355	76.11649	100	100
Karnal	29.893351	76.916606	100	100
Rohtak	29.033765	76.671489	100	100
Total (1000)			**500**	**500**

IV. RESULTS ANALYSIS

The Pesnet preprocesses the images by adding a gaussian filter and greyscale them before predicting the appropriate label for each image. But for this dataset the transfer learning models used to predict human gender was the NasNet, Inception-Residual NetworkV2, VGGNet19, InceptionV3,VGGNet16 and ResNet50. Input to these models for classification were resized greyscale images. 224 × 224 pixels were the reduced size of the input photographs for the Pesnet. Pesnet and all Every pretrained transfer learning models were trained over 50 epochs.
According to experimental data, As image sizes grew, the model's variance toward the class of both males and females rose.. The sizes used for the experiment were 224 x 224, 299 x 299, and 180 x
180. Nevertheless, no appreciable benefit was obtained from this modest trial increase. In the end, 224×224 emerged as the top model with a wider range of inferences and edge case performance, which was difficult for the pretrained model since it was unable to discern between samples for classes like Male and Female.
Based on a close examination of Table 8, we can conclude that Pesnet have the F1 score of 0.96
,which confirms effectiveness of our suggested model, whereas all pre-trained models were unable to correctly predict the Gender (i.e., had an F1 score of 0). Pretrained models such as VGG16, VGG19, and NasNet shown large variation between classes and were unable to acquire global variables like foot size and shape, which were crucial for determining a person's gender. Table 8 allows us to concentrate on Pesnet's performance, which surpasses other architectures by 79–90% Its reliability across the dataset is demonstrated in terms of "gender" correctness, which aids in benchmarking our findings. This demonstrates its value in comprehending the ridge pattern, the separation between the two humps, and the footprint's size—all of which are key markers for predicting a person's gender.

Additionally, in the early phases of architectural design, the model was becoming overfit on the female class. The model benefited considerably from the combination of sets 1 and 2 as well as the insertion of a convolutional layer in a fixed structure. The main accomplishment was the adoption of Pesnet, which not only improved the results in many ways but also assisted in addressing the dataset's class imbalance. It should be mentioned that the training accuracy increased significantly when the two thick layers were added before the output layer. Higher levels of intrinsic characteristics that are exclusive to each footprint were better understood because to the thick layers.
The amount of environmental noise was reduced with the use of preprocessed photos, and it was simple to identify the region of interest. Since the data was impacted by dirt, accessories, and natural illumination, the use of greyscale was essential in reducing mistakes that can be harmful in the categorization label determination process and identifying just the essential details required for predictions. As a result, Pesnet's testing accuracy on the dataset establishes a standard for the various architectures that may be used to forecasts.
According to experimental data, the Model encountered some increase in variance toward the both the class of males and females as image sizes increased. 150×150, 200×200, 224×224, 250×250, and 256×256 were the sizes used in the experiment; nevertheless, this incremental increase in size did not result in any appreciable improvement. With more varied inferences and better performance at the edge cases—a major problem for the pretrained model as it was unable to discern between samples of Female and Male—224×224 ultimately emerged as the top model. Upon closely examining Table 8, We can draw the conclusion that none of the pretrained

models could accurately predict the gender. (eg., had an F1 score of 0). In contrast, PesNet's F1 score of
0.96 confirms the effectiveness of our proposed model. The models which are pretrained, such as NasNet, VGG19, and VGG16 had large variation for the various classes and were unable to learn global variables, such as foot size and shape, which were crucial for determining a person's gender. Figures 5 through 11 illustrate how the various pretrained CNN network models' accuracy and loss evolve as iterations and duration increase. The VGG16 model clearly performs better than any other transfer learning architecture in terms of gender prediction accuracy. Other models (NasNet, VGGNet19,ResNet50, Inception-Residual Network,InceptionV3,) only predict gender with an accuracy ranges from 47 to 59 percent. The F1 scores of the female class should be the primary emphasis for gender prediction since, with the exception of Pesnet, none of the designs were able to surpass even a 0.50 score, demonstrating the models' lack of flexibility and supporting the conclusions of our suggested architecture. The

size and form of the footprints clearly distinguish male and female footprints from one another Consequently, the pretrained models' inability to learn both the visible global characteristics and the smaller features while forecasting the results causes them to perform poorly on these real-world samples. Thus, many corner situations that could have been challenging for the other neural network designs to recognize and comprehend were removed thanks to the preprocessed pictures and the application of the Kalman filter in Pesnet.
The findings of Table 8's evaluation of Pesnet's cumulative gender identification skills demonstrate an accuracy of 96%, which is a key sign that Pesnet is the most qualified candidate to handle the dataset and related data. Other models' performance is imprecise and unreliable.

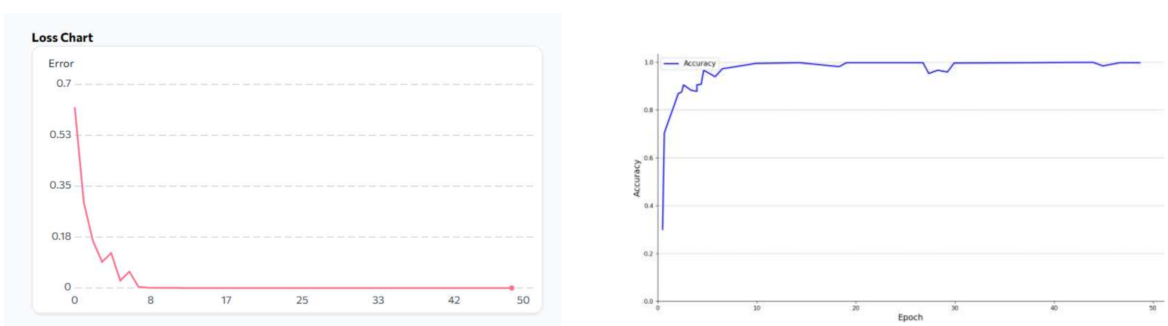
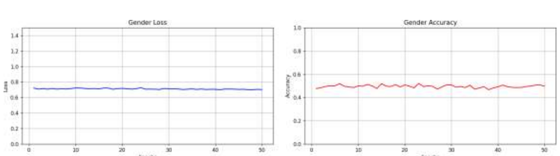
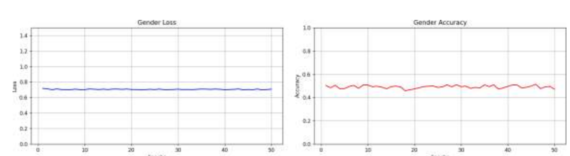


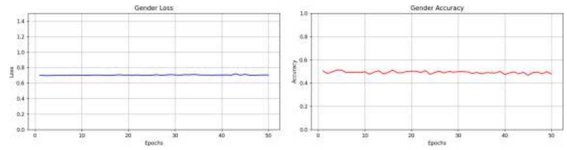
Fig. 5: loss and accuracy of PesNet during training

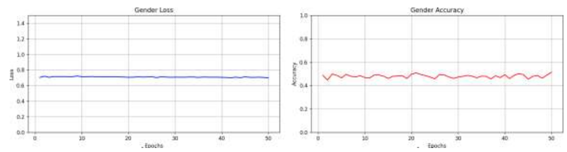


(a) Loss and Accuracy of InceptionResNetV2

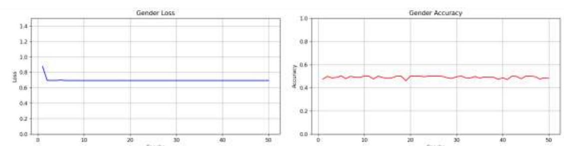


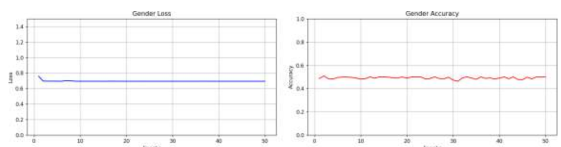
(b) Loss and Accuracy of InceptionV3





(c) Loss and Accuracy of NasNet (d) Loss and Accuracy of ResNet50





(e) Loss and Accuracy of VGG16 (f) Loss and Accuracy of VGG19ig. 6: ccuracy nd loss for different models during training

V. RESULT AND DISCUSSION

This research work creates a deep convolutional neural network model using 29 distinct layers that adhere to a predetermined scheme i.e. Conv2d Set1 and Set2 as previously mentioned inspired from Tensor Flow deep learning architecure via keras to automatically recognize the gender of human being from their footprint. The study was arcane on the grayscale human bare footprint image. The gender prediction findings of the research were 96%. In general, the accuracy of genders of human being prediction by Pesnet is very good.

TABLE VII: Precision, Recall, F1 Score and Accuracy of Model for gender classification

SN	**Models**	**P Male**	**P Female**	**R Male**	**R Female**	**F1 Male**	**F1 Female**	**Accuracy**
1	Pesnet	0.98	0.94	0.94	0.98	0.96	0.96	96%
2	VGG16	0.5	0.00	1.00	0.00	0.66	0.00	50%
3	VGG19	0.00	0.5	0.00	1.00	0.00	0.66	50%
4	InceptionV3	0.49	0.48	0.80	0.18	0.61	0.26	49%
5	ResNet50	0.49	0.49	0.74	0.24	0.59	0.33	49%
6	NasNet	0.52	0.51	0.34	0.68	0.41	0.58	51%
7	InceptionResNet V2	0.47	0.48	0.34	0.62	0.39	0.54	50%

We used six different architecture i.e. , VGG19 ,InceptionV3, InceptionResnetV2, ResNet50 VGG16, VGG19. directly on the footprints images of human beigns in this work also. These well-known architectures were used clearly in various areas of science and technology and thus assisted us in benchmarking Pesnet results. These architectures were better-performing than our model in footprint identification of human beign where accuracy and F1 score was lesser and thus helped us in getting to our inferences and coming with our final conclusion. The development environment was Google Colab Pro and the model was trained using Nvidia T4 GPU with 16 GB RAM.

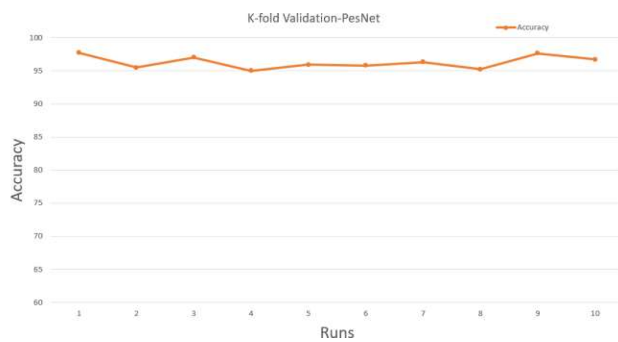


Fig. 7: K-fold Validation for PesNet

We used k-fold cross-validation on PesNet in order to fully comprehend the outcomes. The validation procedure produced dependable and consistent results, with little fluctuation in accuracy across various folds, as the figure shows. This suggests that our design exhibits a high degree of resilience and supports the model's stability and dependability. The k-fold validation findings offer compelling proof that PesNet is robust and can sustain performance consistency, establishing it as a reliable option for the given job.

TABLE VIII: showcasing model loss and training accuracy

SN	Architectures	Training accuracy	Training loss	Input size
1	PesNet	100.00%	0.011	224×224
2	VGG16	48.14%	0.6933	224×224
3	VGG19	50.00%	0.6932	224×224
4	InceptionV3	47.14%	0.7075	299×299
5	ResNet50	51.39%	0.6981	224×224
6	NasNet	47.14%	0.7036	299×299
7	InceptionResNetV2	49.73%	0.7029	299×299

Attention point: as per our knowledge no study has done identification of gender on footprints with so much size of data of 1000. The primary challenge concerning this type of research was related to data collection and data annotations. Honetsly we arranged for around 1000 samples inspite of scanning and covencing people for their consent is really not an easy task. There is also very slight dimorphism in the size of male and female which make manual analysis and annotation of the samples very difficult. Mostly researches on human foot prints analysis uses manual features to identify the individual . In order for the architecture to naturally comprehend the important features and determine a person's gender based on their bare footprints, we employed deep CNN in our work. In future we can collect more samples to achieve an better accuracy. The Pesnet can help in identifying individuals from there footprint very quickly and with less efforts and less manpower and in a cheaper way.

VI. ACKNOWLEDGMENT

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