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Morphopod: A Convolutional Neural Network Architecture for Predicting Human Age Based on Footprint Analysis

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Abstract

Identifying human age based on Footprints is a complex task, primarily due to the absence of comprehensive datasets. To tackle this issue, we have developed a dataset divided into four distinct categories. Our initial strategy involves using pre-trained models to apply transfer learning, training on RGB images of human footprints from the dataset for classification. This paper introduces Morphopod, a custom Deep CNN architecture optimized to outperform tradi- tional pre-trained models. By addressing challenges like data imbalance, which often under- mines the success of pre-trained systems, Morphopod offers a more reliable solution. It employs Gaussian filtering applied to annotated images as inputs, significantly reducing environmental interference, noises, and achieving better accuracy. This architecture serves as a foundational step for solving footprint-based human identification tasks and holds potential for various other applications in this domain.

Keywords: Deep CNN; Morphopod; Human Footprints; Age; Identification

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1 Introduction

A crucial, multidisciplinary area, forensic science is essential to criminal investigations and court cases. It entails using cutting-edge scientific ideas and techniques to evaluate evidence, investigate crimes, and provide accurate information in court [1]. A crucial component of forensic science is personal identification, especially when dealing with unidentified human remains or people attempting to conceal their identities [2].

Forensic anthropology is based on techniques like anthropometry, DNA analysis, odontology, fingerprinting, biometrics, and lip prints that are essential to personal identification [3]. These techniques assist in extracting important attributes that are essential for verifying an individual's identification, such as height, ethnicity, gender, and age [3]. The integration of these diverse forensic methods allows thorough and trustworthy identification, supporting the legal system and assisting in the settlement of missing people situations [4].

The definitions of ”footprints,” ”foot,” and ”bare footprints” vary across the literature, and it's critical to comprehend these differences in the context of forensics. While ”foot” refers to the full anatomical structure, including the skin [5], ”footprint” can refer to either two-dimensional or three-dimensional shoe prints [6]. Using contrasting colored materials on a different backdrop, the phrase ”bare footprints,” which is used in forensic podiatry, describes the visible prints produced by the undersole's friction ridges [7]. The distinct arrangement of ridges in bare footprints might function as an individual identification, much like fingerprints [8].

At crime scenes, bare footprints are especially significant because they can offer crucial evidence that connects a perpetrator to a particular area, particularly in situations like sexual assault or homicide [9]. Footprints can provide important information on stature, weight, sex, and mobility, as well as aid in the identification of people by examining traits including shape, size, and orientation [10][11][12]. According to certain research, specific characteristics of bare footprints can reveal sexual dimorphism and help identify a person's sex[13][14]. All things considered, forensic analysis of bare footprints aids in verifying a person's presence at a crime scene and has a big impact on how investigations proceed [15][16][17].

The seven techniques for assessing bare footprints are divided into two groups based on recent research. While Group 2 contains strategies for diagnosing foot diseases or categorizing foot types (based on selection criteria), Group 1 include methods for individual typographic characterisation utilized for identification [18]. These two groups, the parameters measured, and the applications, goals, accuracy, dependability, and distinguishable features of the approaches are described in Table 1.1.

Table 1: Bare footprints assessment techniques, parameter measure type, reliability, and use.

Method Name	**Purpose**	**Identifiable Charac- teristics**	**Accuracy (%)**	**Reliability (%)**	**Type of Mea- surement**	**Notable Charac- teristics**
Overlay Method	Identification and foot type	Age, sex, weight	Subjective; relia- bility varies	Varies widely	Morphological outline tracing	Traces known footprint outlines over questioned prints for visual comparison.
Rossi's Podosmet- rics	Foot type clas- sification	Foot type, potential pathologies	Not specifically validated for forensic use	Not applicable	Linear m ea- surements	Uses a grid of lon- gitudinal and trans- verse lines; primar- ily for clinical use.
Reel Method	Identification	Age, sex, weight	95%	95%	Linear and an- gular measure- ments	Incorporates additional measure- ments; shown to have high reliabil- ity.
Optical Ce ntre Method	Identification	Age, sex, weight	85% (estimated)	Lower reliability compared to Gunn and Reel methods	Linear m ea- surements	Assigns an optical center to morpho- logical features; de- veloped by RCMP.
Gunn Method	Identification	Age, sex, weight	90%	90%	Linear m ea- surements	Constructs lines from heel to toes; widely used but originally anecdo- tal.

Geometric Mor- phometric Method	Foot type clas- sification	Foot type, potential pathologies	Not specifically validated for forensic use	Not applicable	Morphological analysis	Uses a comprehen- sive set of land- marks to analyze footprint shape.
Robbins Method	Identification	Not applicable	Not applicable	Not applicable	Visual anthro- pological mea- surements	Combines diag- onal and parallel axis meth ods; discredited due to controversy.

The table-1 provides an overview of footprint assessment methods with an emphasis on categorization and identification. Individual identification is highlighted through the use of linear measuring methods, some of which are very accurate and dependable for forensic applications. Some concentrate on morphological analysis or footprint categorization, whereas some older techniques are less popular because of doubts over their validity and dependability [19].

Techniques for footprint analysis are useful in forensic investigations, but they have some limitations. These include variations in footprint quality brought on by environmental factors, subjectivity in expert analysis that might result in biases, and measurement errors associated with various methodologies. Furthermore, because many methods require entire prints, it may be challenging to correctly evaluate partial prints. The fact that footprints often show class qualities instead of unique individual attributes complicates individualization, and the statistical validity of certain methods is questionable. The lack of defined processes and technical limitations further impair the dependability of these approaches [19]. The following is one method for writing merits: The bulk of the footprint analysis will be carried out using the antiquated, traditional methods, which are sometimes challenging and time-consuming and have a number of disadvantages [19][20], as indicated in Table 2. Our approach uses a deep Convolutional Neural Network to identify the footprints.

CNN has recently overcome the drawbacks of conventional techniques. One CNN model for identifying people from footprints was proposed by a team of academics in 2019. An accuracy of more than 95% was attained by them using a dataset of 30 people [21]. To determine age, gender, and weight from pictures of human tongues, another investigation was conducted. The accuracy of the deep CNN models was more than 75% after they were trained on a sizable sample of 10,590 people [22].

An automated age and gender identification method based on dental orthopantomograms (OPGs) was developed after another research was conducted to determine age and gender. It was able to estimate gender with 96% accuracy and age with 97% accuracy using a dataset of 1,142 digital

X-rays [23].

Similar to research in other fields, such as deep learning-based plant leaf feature extraction, footprint identification might also be viewed as a pattern recognition task. In the medical profession, similar techniques are employed to identify patterns of sickness in CT and MRI scans [24]

Our work focuses on identifying people from bare footprints using deep learning classification. Classification of Age with footprints is a challenge for us. Inspired by the state-of-the-art pretrained models, our first approach trains the images from our dataset using Transfer Learning.

In this work, we provide a new strategy that questions the effectiveness of conventional techniques and huge pretrained models. We introduce Morphopod, an improved and optimized Deep CNN architecture that produces better age-group predictions using Gaussian filtered and greyscaled an- notated photos as inputs. In comparison to pretrained models, the Gaussian filter improves perfor- mance by reducing ambient noise in each image. Our suggested design also tackles the problem of class imbalance, which was a major drawback in a number of pretrained models.

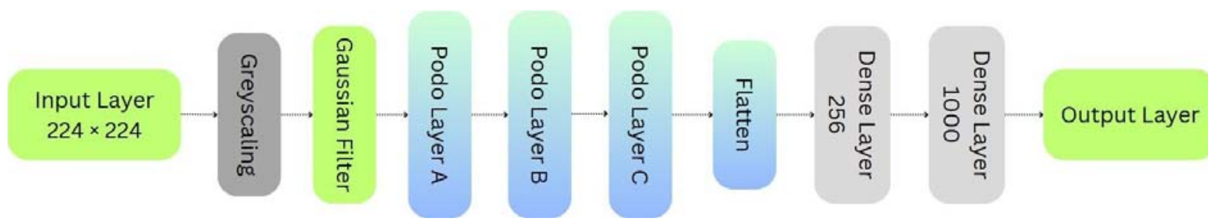


Figure 1: Architecture of Morphopod.

Overview to Morphopod

The specific contributions of our work are as follows:

- We present MorphopodLayers to Construct the Morphopod model for extracting fine details. Morphopod- Layer has been shown to effectively capture side edges and reduce noise.
- A lightweight design called Morphopod reduces the training process's computing complexity.

This paper is organized as follows: The data description is given in Section II, the technique and suggested architecture are explained in Section III, the experimental findings are given in Section IV, and the results, their uses, and future directions are covered in Section V.

2 THE PROPOSED APPROACH

A. Detail of MorphopodLayer

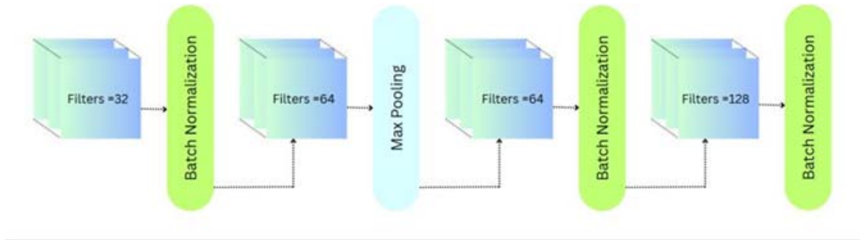
Morphopod incorporates three distinct types of layers— MorphopodLayer-A, MorphopodLayer-B, and MorphopodLayer-C, as shown in Fig. 1. Each of these layers consists of con- volution layers (Convolution-4, Convolution-3, Convolution-2, and Convolution-1), three levels of batch normalization, and one layer of Max-pooling. The convolution layers in each MorphopodLayer utilize different filter sizes, as detailed in Table 3. The number of filters in each layer dictates the extraction of both local and global features from the raw footprints, as outlined in Table 3. MorphopodLayer-A is designed to capture fine details of the bare footprint, while MorphopodLayer-B and MorphopodLayer-C focus on extracting global features.

Table 2: Filters utilized in each convolutional layer across the MorphopodLayers.

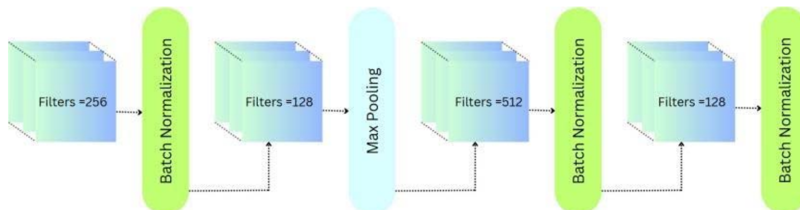
S/N	Morphopod-Layer	Convolution-4	Convolution-2	Convolution-3	Convolution-1
1	MorphopodLayer-A	128	64	64	32
2	MorphopodLayer-C	128	128	256	256
3	MorphopodLayer-B	128	128	512	256

The combination of batch normalization, convolution, and max-pooling in every layer is essential for capturing both large-scale features, such as variations in size and internal characteristics (like the distance between humps), as well as finer details, including edges, shape, and size of the footprints. Additionally, problems like disappearing and ballooning gradients are lessened by the use of batch normalization. In Morphopod, each convolution layer uses a 3×3 filter size to capture intricate details. Table 4 shows the performance of Morphopod with different filter sizes, revealing that accuracy decreases as the filter size increases. However, the highest accuracy is achieved with a 3×3 filter size and grayscale images, which is why the MorphopodLayer is designed with a 3×3 filter size."

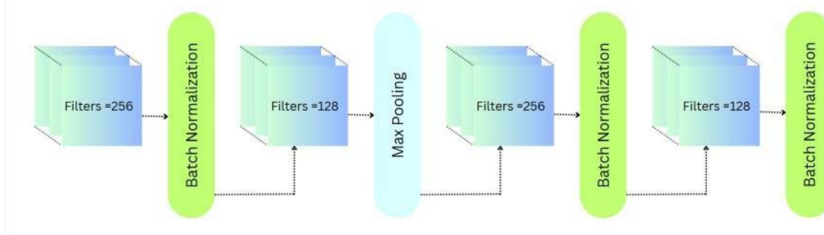
Morphopod draws inspiration from spatially optimized architectures like AlexNet and LeNet, as well as depth-based CNN architectures such as Inception and ResNet. The primary goal behind Morphopod is to develop an innovative model that can analyze the boundaries of human bare foot- prints and identify key features, enabling the classification of different age groups. To achieve this, Morphopod is structured using MorphopodLayers, which are specifically designed to extract relevant features from human footprints.



(a) Morphopod Layer-A



(b) Morphopod Layer-B



(c) Morphopod Layer-C

Figure 2: The block diagram of the Morphopod Layers.

Table 3: MorphopodLayer's performance with varying filter sizes.

S/N	Size of the Filter	Morphopod's Accuracy
1	7 × 7	57.00%
2	5 × 5	51.14%
3	3 × 3	69.00%

As shown in Fig. 1, the suggested Morphopod is composed of input and output layers as well as three different types of MorphopodLayer: MorphopodLayer-A, MorphopodLayer-B, and MorphopodLayer-
C. The model begins with an input layer that takes in a 224 × 224 resolution picture. The three MorphopodLayer types are then used to process this input picture, as shown in Fig. 1. Morphopod uses the ReLU activation function to capture the non-linearity of the model.

Table I illustrates how the number of filters in each layer progressively rises. The model was able to capture various amounts of global characteristics thanks to this variety in filter widths. First, local information was gathered using smaller filters, and then the size and shape of the footprint were extracted using bigger filters. To improve accuracy, two completely linked thick layers were added, each with 256 and 1000 neurons. It has been shown that employing two successive thick layers with fewer neurons is effective. Additionally, detecting edge situations was aided by mixing three different kinds of PodoLayers.

Table 4: Performance of the Morphopod with varying Epochs.

S/N	Number of Epoch Cycle	Accuracy
1	20	51%
2	50	69%
3	100	34%

Table 4 illustrates the performance of Morphopod with varying epoch cycles. It is observed that the model achieves the best performance at 50 epochs, with performance declining as the number of epochs increases (indicating overfitting) or decreases (indicating underfitting). Therefore, the proposed Morphopod was trained for 50 epochs to achieve optimal results.

3 DETAILS OF THE DATA USED IN THE ANALYSIS

Five administrative divisions of Haryana, India—Faridabad, Gurugram, Hisar, Karnal, and Rohtak—were used to collect photographs of human bare footprints. Participants were required to complete consent forms granting permission for their data to be used. The sites of sample collection and the count of 21-30, 31-40, 41-50 and 51-60 samples from each division are listed in Table 6. To create the dataset, the photos were scanned at 300 DPI using an Epson flatbed scanner and stored on a laptop. The same process was used to scan each image. Images of 1000 human barefoot footprints were gathered, 500 of which came from male participants and 500 from female participants. The people who took part were between the ages of 18 and 60. The initial photograph of the footprints were compared with the suggested photos to check for annotation errors. Images are then subjected to additional pre-processing. which serve as feedback for the architecture we have in mind.

Table 5: Displaying the Indian data collecting sites.

S/N	District	Latitudes	Longitudes	21-30	31-40	41-50	51-60
1	Faridabad	28.387218	77.298655	40	50	50	50
2	Gurugram	28.441302	77.020682	50	55	50	50
3	Hisar	29.599355	76.11649	50	55	50	50
4	Karnal	29.893351	76.916606	50	50	50	50
5	Rohtak	29.033765	76.671489	50	50	50	50
			Total (1000)	**240**	**260**	**250**	**250**

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Table 6: An overview of the selected dataset for barefoot prints

S/N	Class	Samples per class	Resolution (DPI)	Image Type
1	Male	500	300	RGB
2	Female	500	300	RGB

(a) Age group of 21-30 (b) Age group of 31-40 (c) Age group of 41-50 (d) Age group of 51-60

Figure 3: Comparison of Footprints of different classes

3.1 Data Analysis

To preprocess the photos, Torchvision, Python, and PIL packages are used. We grayscale the images and apply a Gaussian filter as part of the preprocessing step. Using Keras, six distinct cutting-edge architectures—ResNet50, InceptionV3, InceptionResnetV2, VGG16, VGG19, and NasNet—are applied to footprint photos in TensorFlow.

4 RESULTS ANALYSIS

The Morphopod operates by preprocessing images through Gaussian filtering and greyscale conver- sion, followed by forecasting the corresponding image labels. However, the transfer learning mod- els ResNet50, InceptionV3, Inception-Residual NetworkV2, NasNet, VGGNet16, and VGGNet19 used resized greyscale images with a kalman filter applied as input to perform classifications on the dataset in order to predict the gender of humans. The input photos for the Morphopod were scaled to 224 by 224 pixels. Every pretrained transfer learning model, including Morphopod, was trained across 50 epochs.

According to the experimental data, the architecture encountered some increase in variations toward the classs as the size of the photos increased. 224×224, 299×299, and 180×180 were the sizes used in the experiment; nevertheless, this incremental increase in size did not result in any appreciable gain. With more varied inferences and better performance in the edge cases, a major problem for the pre-trained model, as it was unable to discern among the samples for classes like

31-40 and 21-30 —224×224 ultimately emerged as the top model. Based on a close examination of Table 8, We are able to determine that entire pretrained Architectures were unable to correctly Estimate the Age (F1 score was 0); in contrast, Morphopod's F1 score's confirms the effectiveness of our suggested model. All pretrained Architectures, such as VGG19, NasNet, and VGG16, had large variation for various classes and were unable to train over global variables, such as foot size and shape, which were crucial for determining a person's gender.

From Table 8, We can concentrate on Morphopod's performance, which performs better than other architectures by 79-90% margin in terms of 'Age' Acuuracy, It helps us assess our outcomes and demonstrates its dependability throughout the dataset. This demonstrates its value in comprehend- ing 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 Age.

The addition of a convolutional layer in a fixed format and the combined usage of sets 1 and 2 significantly benefited the model, since our model was also being overfitted on the ”31-40” class because there were more training examples of these particular labels in the initial stages of archi- tectural design. The main accomplishment of all was the inclusion of Morphopod, which not only improved the results manifold 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 specific to each footprint were easier to interpret because to the thick layers.

When preprocessed photos were used, the amount of background noise was reduced and it was simple to identify the area of interest. Given that the data was impacted by natural sunlight, dirt, accessories, and other factors, the use of greyscale images and gaussian filtered images was essential in reducing mistakes that may be harmful in the categorization label determination process and identifying just the essential points required for predictions. As a result, the testing accuracy that Morphopod attained on the dataset establishes a standard for the other prediction models.

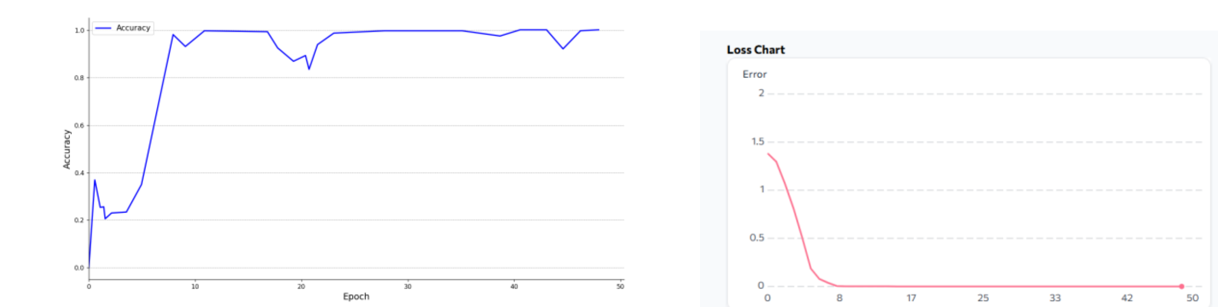

Figure 4: Accuracy and Loss of Morphopod

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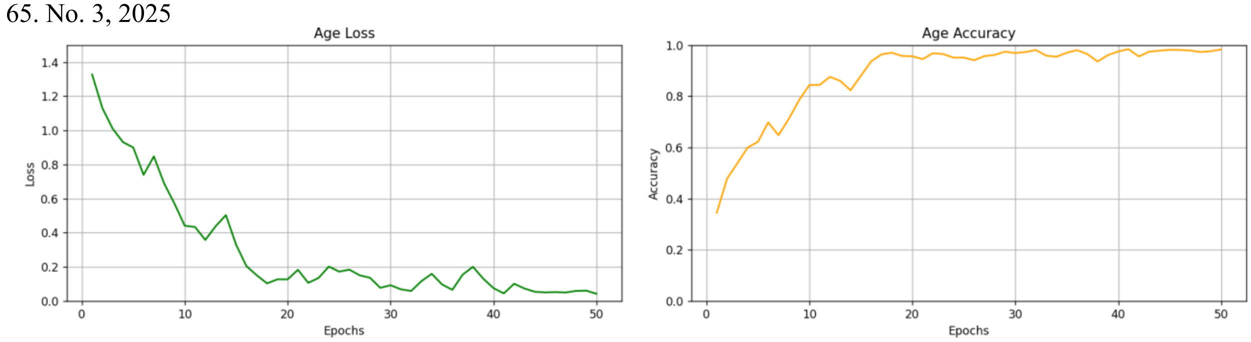

Figure 5: Loss and Accuracy of InceptionResNetV2

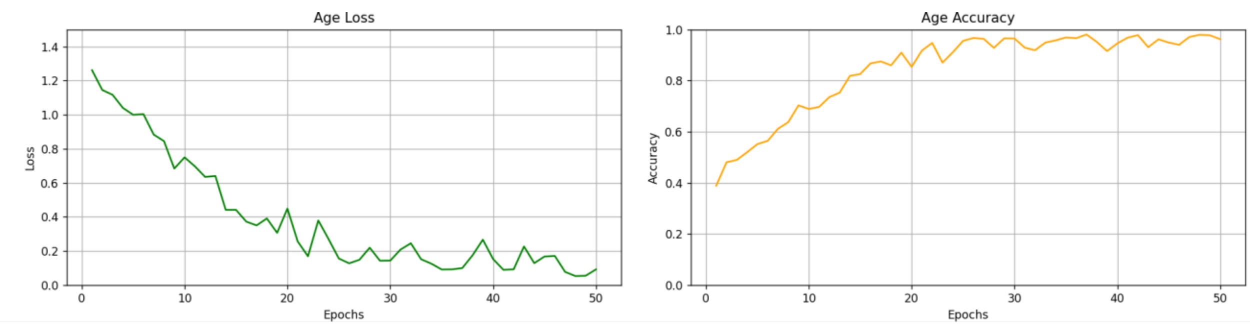

Figure 6: Loss and Accuracy of InceptionV3

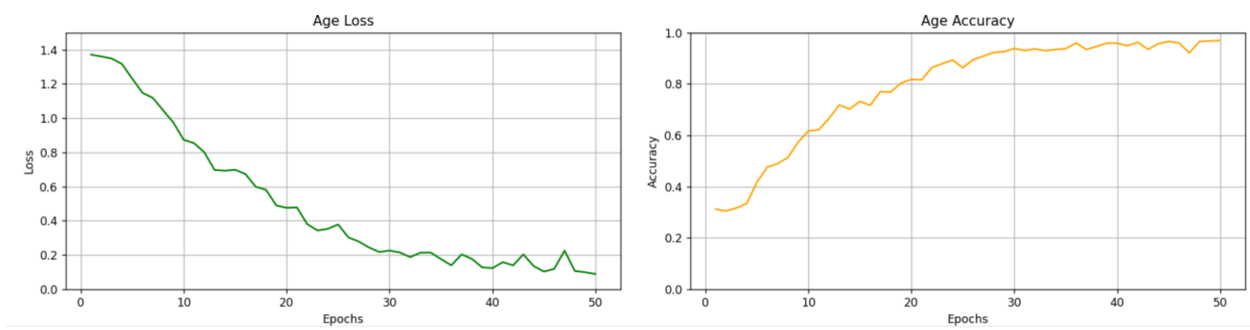

Figure 7: Loss and Accuracy of NasNet

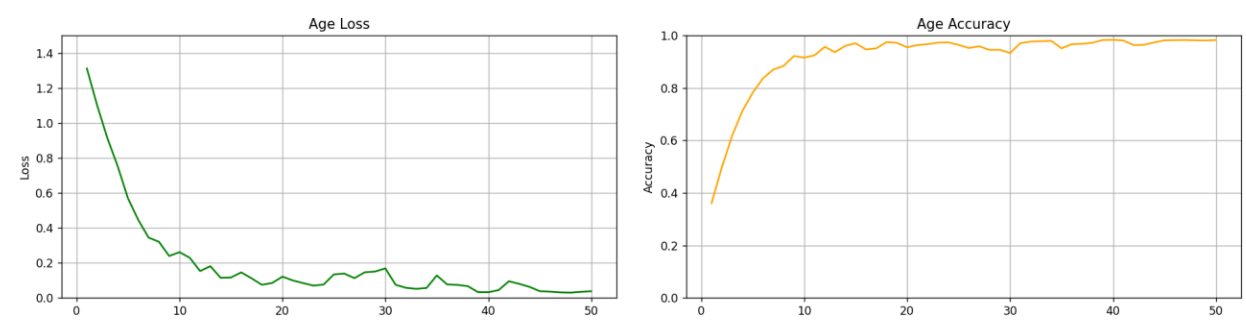

Figure 8: Loss and Accuracy of ResNet

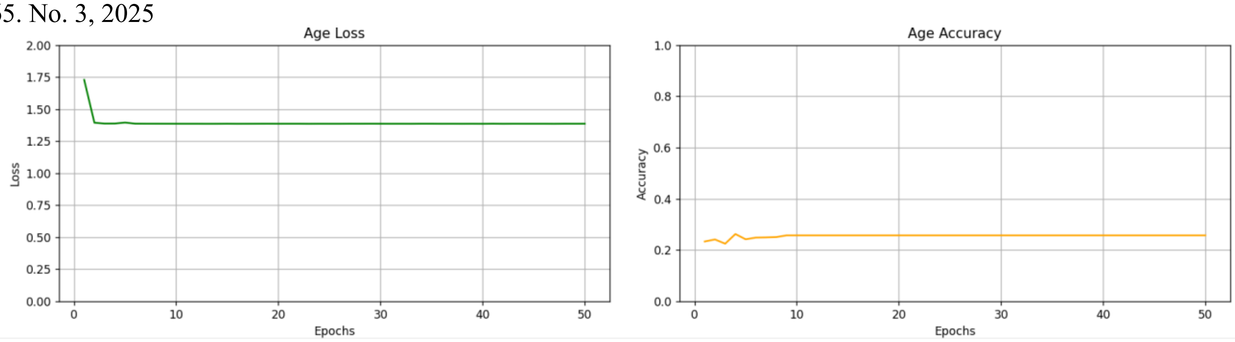

Figure 9: Loss and Accuracy of VGG16

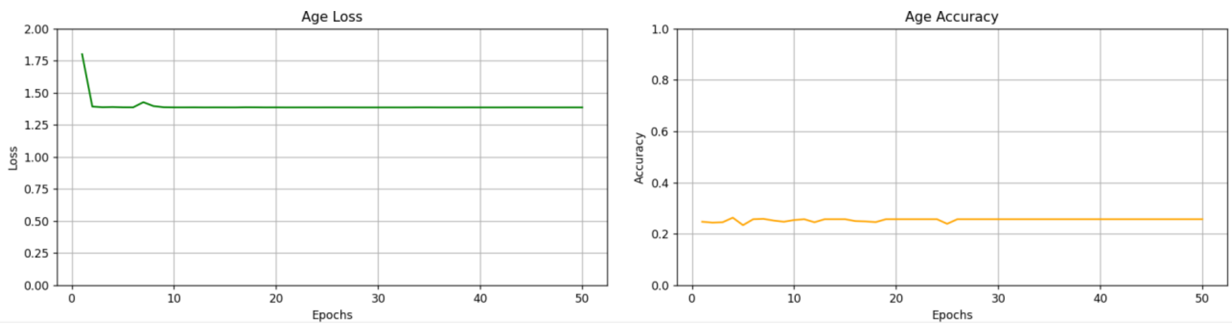

Figure 10: Loss and Accuracy of VGG19

The accuracy and loss of the different pretrained convolution neural network models change with increasing epochs and length, as shown in Figures 5 to 11. In terms of age prediction accuracy, it is clear that the ResNet50 model performs better than any other transfer learning architecture. Based on Table 8, the accuracy of the other architectures (VGG16, NasNet, InceptionV3, Inception-Residual Network and VGGNet19) in focus to predict age falls between 22% and 49.18%.

When predicting age, the classes' F1 scores should be the main focus because, with the exception of Morphopod, none of the architectures were able to set a basic benchmark, demonstrating the models lack of flexibility and supporting the conclusions of our suggested design. Because the size and shape of the footprints clearly differ between different age group's footprints, Because the pretrained models cannot learn both the visible global properties and the finer features while generating predictions, they perform poorly on these real-world data. As a result, many edge in- stances that could have been challenging for alternative neural network designs to recognize and comprehend were removed thanks to the preprocessed pictures and the Gaussian filter in Morphopod. Table 8 assesses Morphopod's ability to determine the cumulative age of samples. The findings reveal an accuracy of 69%, which is a significant sign that Morphopod is the most capable candidate to handle the dataset and associated data. Other models performance is imprecise and unreliable.

5 RESULTS & DISCUSSION

In this study, deep CNN Model employing 28 distinct layers and a predetermined plan known as Conv-2d Set1 and Set2. earlier mentioned, is proposed to automatically identify a person's Age from their Footprints. It is inspired by the Tensor Flow's deep learning structure using Keras. Greyscale photos of bare human footprints were used for the investigation. The research findings showed that 69% of the age estimations were correct. All things considered, Morphopod predicts human age with a fairly high degree of accuracy.

Table 7: Precision, Recall, F1 Score, and Accuracy of various Models

	Precision				Recall				F1 Score				
Architectures	21-30	31-40	41-50	51-60	21-30	31-40	41-50	51-60	21-30	31-40	41-50	51-60	Accuracy
Morphopod	0.75	0.60	0.83	0.68	0.60	0.48	1.00	0.68	0.66	0.53	0.90	0.68	69.00%
VGG16	0.00	0.00	0.27	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.42	0.00	27.02%
VGG19	0.00	0.00	0.27	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.42	0.00	27.02%
InceptionV3	0.00	0.00	0.23	0.14	0.00	0.00	0.76	0.07	0.00	0.00	0.36	0.09	22.43%
ResNet50	0.68	0.41	0.34	0.51	0.66	0.34	0.31	0.65	0.67	0.37	0.32	0.57	49.18%
NasNet	0.63	0.26	0.38	0.59	0.28	0.32	0.62	0.39	0.39	0.29	0.47	0.46	41.35%
InceptionResNetV2	0.69	0.29	0.39	0.61	0.44	0.37	0.40	0.65	0.54	0.32	0.39	0.63	47.02%

Table 8: The Accuracy and Loss of various Architectures while training

S/N	Name of Architecture	Accuracy	Loss	Size of Input Images
1	Morphopod	100%	0.0110	224×224
2	VGG16	25.76%	1.3864	224×224
3	VGG19	25.76%	1.3861	224×224
4	InceptionV3	96.22%	0.0927	299×299
5	ResNet50	98.34%	0.0372	224×224
6	NasNet	96.95%	0.0897	299×299
7	InceptionResNetV2	98.27%	0.0429	299×299

Additionally, we used six distinct state-of-the-art architectures—ResNet50, InceptionV3, InceptionResnetV2, VGG16, and VGG19—directly to the footpint pictures of human behavior in this study. These well-known designs have clearly been applied in a variety of scientific domains, which enabled us to compare the outcomes of Morphopod. These architectures' accuracy and F1 score in identifying human footprints were lower than our model's, which helped us draw our findings and arrive at our inferences. Google Colab Pro was the programming environment employed and the model was trained on a T4 GPU with 16 GB of RAM.

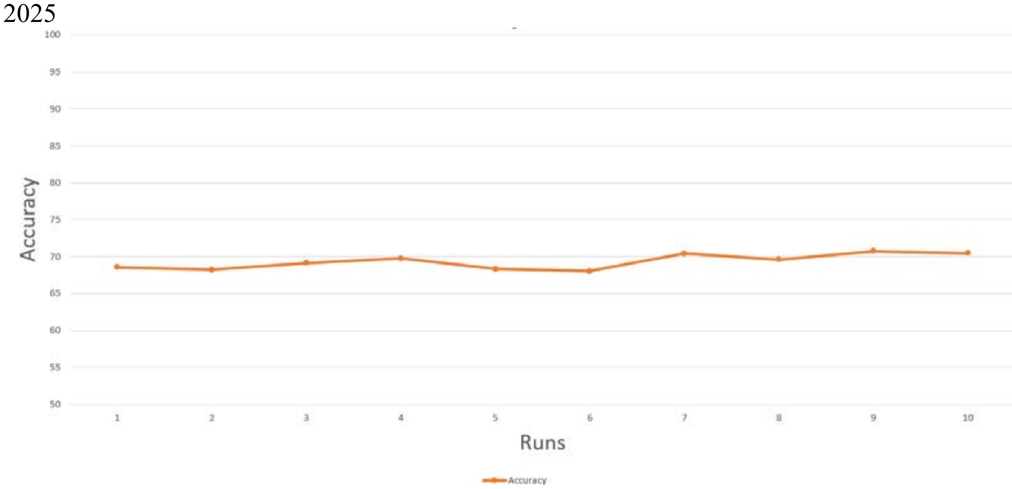

Figure 11: K-fold Validation of Morphopod

To gain a comprehensive understanding of the results, we conducted k-fold cross-validation on Morphopod. As illustrated in the figure, the validation process yielded consistent and reliable out- comes, with minimal variation in accuracy across different folds. This reinforces the reliability and stability of the model, suggesting that our architecture demonstrates a high level of robustness. The results from the k-fold validation provide strong evidence that Morphopod is capable of maintaining performance consistency, making it a dependable solution for the task at hand.

To the best of our knowledge, no study has used footprints with a data size of 1000 to identify age. Data collection and annotation was the biggest obstacle for this kind of study. Even though scanning and persuading individuals to provide their consent is a difficult process, we managed to organize 1000 samples.It is quite difficult to manually assess and annotate the samples since the footprint sizes of the various age groups vary so little in the photos. The majority of studies on the analysis of human footprints employed manual attributes to determine the individual.In order to make the architecture naturally comprehend the important features and estimate a person's age based just on their bare footprints, we employed deep CNN in our work. One of our work's limi- tations is the tiny dataset sample size. To improve accuracy, we want to gather additional samples in the future.It may be possible to identify people from their footprints more rapidly, cheaply, and with less effort and labor thanks to Morphopod.

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