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RESEARCH ARTICLE

Ensemble-Based Hybrid Transfer Approach for an Effective 2D Ear Recognition System

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ABSTRACT Person identification using ear images has gained significant attention recently. Transfer learning provides an effective platform for image classification, utilizing CNNs like AlexNet, ResNet, VGG16, and VGG19, which are fine-tuned for specific applications. Combining transfer learning with support vector machines (SVM) enhances people recognition via ear images. This paper integrates a hybrid transfer learning model with an ensemble technique to improve recognition accuracy. We use pre-trained CNN models, VGG16 and VGG19, for feature extraction and replace the fully connected layer with an SVM classifier. Using the SoftMax activation function, each model generates a probabilistic output, which is averaged for classification. The proposed ensemble model was validated on two datasets with variations in pose, illumination, and rotation. Simulation results show that the ensemble-based transfer learning approach outperforms its two anchor models and competes with state-of-the-art ear recognition techniques.

INDEX TERMS Ensemble learning, transfer learning, feature extraction, classification, accuracy.

I. INTRODUCTION

Person identification using ear images has become an ever-growing need in recent years due to its vast applications in security, surveillance systems, and forensic investigation. Deep learning-based approaches that leverage ear images have demonstrated remarkable performance for person recognition [1], [2], [3]. These techniques effectively extract robust features from ear images and determine relevant information, enabling accurate features classification. Researchers have introduced various methodologies and datasets, with a primary focus on utilizing ear biometrics for individual identification [1]. Their work spans techniques ranging from holistic approaches to deep learning, accompanied by comprehensive explanations of both constrained and unconstrained ear image datasets. The traditional machine learning algorithms perform image classification tasks by training each classifier separately whereas the transfer learning approaches use cross-domain learning techniques [4]. Zarachoff et. al. in [5], [36], presented a multi-image generation methodology, which they applied to still grey images and high-frequency wavelet subbands of the grey images. They then employed PCA to extract ear image features from the resulting multi-images. They experimentally showed that their methods outperformed conventional anchor PCA-based and other state-of-the-art statistical methods, generating competitive performance to those of learning-based methods at a fraction of the computation cost without needing to be trained. The intuition behind the deployment of the transfer learning technique is to pass the knowledge from one field to another related field. However, the major challenge associated with this approach is to prevent the transfer of wrong information and to guarantee the transfer of correct information since the performance of the new system is massively dependent upon the transfer of positive knowledge.

Khaldi et. al in [6] conducted research on ear recognition by applying an image coloring method to a Generative Adversarial Network (GAN) model. Their study employed unsupervised learning techniques across three distinct datasets: University of Science and Technology Beijing (USTB2), Annotated Web Ears (AWE), and Mathematical Image

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Analysis (AMI). The resulting recognition accuracies were: 51.25%, 100.00%, and 98.33%, respectively. In a separate investigation, Lei et al. [7] validated their work using the SSD MobileNet v1 model with the USTB dataset, achieving an accuracy exceeding 99%.

Mehta et al. [8] proposed an ensemble approach that combined lightweight CNNs with popular pre-trained models such as VGG16, VGG19, and DenseNet201. Their classification task involved identifying 221 different individuals based on their ear images. By extracting deep features from various pre-trained models and lightweight CNNs, they fine-tuned the classification process at fully connected layers. Their findings underscore the effectiveness of utilizing two different types of CNN models (lightweights and pre-trained) in the domain of ear recognition, resulting in robust performance. Additionally, Chowdhury et al. in [9] leveraged handcrafted features for robust ear recognition, achieving a recognition accuracy of over 98%. In their study, Alshazly et al. [10] utilized domain adaptation techniques to address the limitations posed by a restricted dataset. They applied deep convolutional neural network (CNN) models, specifically ResNet, ResNeXt, Inception, AlexNet, and VGGNet, to the unconstrained EarVN1.0 dataset. Their fine-tuning strategies resulted in state-of-the-art recognition performance on this demanding dataset.

Zarachoff et. al applied a combined approach of Multi-Banding and Support Vector Machine (CERMB-SVM) to perform ear recognition [11]. They split the input image into different bands and applied canny edge detection techniques to extract the edge portion in each band. The binary edge maps are generated corresponding to the ear shape in each band. The generated binary edge maps are then combined to create a single binary edge map. The resulting edge map is divided into non-overlapping cells which are used to create the Freeman chain code corresponding to each cell. By taking four contiguous cells, a histogram is computed which is then normalized and linked together to create a chainlet for the input image. These created chainlet histogram vectors are utilized for the training and testing of a pairwise Support Vector Machine (SVM). Their approach achieves 99.02% and 99.44% accuracy on two benchmark datasets IITD-II and USTB-I respectively.

Shaha and Pawar in [12] introduced a hybrid model for image classification. They employed a VGG19 model as pre-trained for deep feature extraction and the SVM for the classification. They compared the performance of their proposed model on three different challenging image datasets, they reported an accuracy of 99% for their proposed hybrid model, which was significantly higher than the other state of the art networks, e.g., AlexNet, and VGG16. However, the application of the hybrid VGG16 and VGG19 and the SVM for ear recognition has not been fully investigated in the literature.

The study at hand harnesses the power of hybrid transfer learning and an ensemble technique, seamlessly integrating both within a single model. For the ensemble aspect, two distinct CNN models VGG16 and VGG19 are employed to extract efficient features. Additionally, SVM classifier is utilized at the final layer of the networks for classification tasks. This ensemble-based hybrid transfer learning approach significantly enhances the accuracy of person recognition using ear images. The authors' contributions in this paper are as follows:

A. INTEGRATION OF SVM CLASSIFIER

The major contribution lies in integrating the SVM classifier with popular deep learning models, specifically VGG16 and VGG19.

B. LEVERAGING BASE MODELS

By utilizing these two base models, VGG16 and VGG19, the system effectively learns task-specific information from input ear images.

C. OVERCOMING LIMITED DATASET LIMITATIONS

The adoption of transfer learning techniques helps overcome the constraints posed by a limited dataset.

D. ROBUSTNESS AGAINST OUTLIERS

The SVM classifier enhances robustness, even in the presence of occlusions caused by hair, earrings, and varying lighting conditions.

E. MITIGATING OVERFITTING

Incorporating dropout strategies and appropriate regularizers prevents the model from overfitting.

To demonstrate the effectiveness of the proposed approach, experiments were conducted on two distinct datasets: one downloaded from Kaggle and the other being the IITD-II dataset. The experimental results reveal that the combined ensemble method achieves superior performance in terms of accuracy. Initial findings from this investigation were originally published in [13], where a single CNN model (VGG16) paired with an SVM classifier achieved a recognition accuracy of 99.23%. Thus, the present work represents an improvement over the previous approach [13].

The rest of the paper is structured as follows: Section II looks at different techniques and architecture of deep learning models; Section III details the dataset and the proposed methodology; the setup for experiments and the proposed models' simulation results are presented in Section IV and the paper is concluded in Section V.

II. RELATED WORKS

With the advancements in communication, technology and digital application, the demand for automated secure authentication systems has increased. Biometric identification systems have been considered as one of the solutions. Ear image is one of the popular biometric modalities, which is widely acceptable under controlled and uncontrolled environmental conditions. It is socially acceptable and its passive and non-intrusive nature provides accurate authentication. Due to the presence of high levels of intra- and inter-class variance in ear image data, traditional algorithms that use hand-crafted features frequently fail due to large datasets. In such circumstances, deep CNNs are widely used and gaining more success.

In the context of the traditional approach, Mehta et. al. proposed a cohort-based technique and applied mini-batch k-means clustering algorithm to perform ear recognition tasks [14]. For feature extraction and matching purposes, they applied oriented FAST and rotated BRIEF (ORB) methods. This approach shows superior result over the non-cohort-based approach. Deep CNN-based approaches process the input images through a series of convolutional layers followed by Max Pooling and a fully connected layer. Thus, in an image-based classification system, different layers of CNN transform an image volume to output in the form of predictions. The volume of training data and the time needed to train the model are the major challenges associated with these CNN models. Insufficient information on data may lead to overfitting problems and reductions in their performance with new sample data [15].

Many researchers tried to solve the overfitting issue by penalizing the loss functions, regularizing the architectures, and by creating synthetic samples [16], [17]. In this context, transfer learning has been proven to be an alternative solution to utilize the popular deep learning model (pre-trained model), which has been trained on a larger dataset for specific tasks [18], [19], [20]. Some pre-trained models like VGG16, VGG19, AlexNet, and GoogleNet are proposed which demonstrate tremendous performance on low-resolution and noisy challenging data [21], [22].

Initially, researchers proposed the AlexNet model to handle tasks related to object recognition [23]. One issue with this CNN model is the training of this model for which the ILSVRC dataset is used which is publicly available. This model requires a deeper network for extracting robust, intrinsic, and complex features. VGG16 model meets these requirements and solves many image-based classification tasks.

Simonyan et. al. proposed VGG16 architecture and analyzed the effect of network depth of convolutional neural network by the accuracy [24]. They found that by increasing the depth to 16-19 weight layers, significant improvement in the classification accuracy is achieved. Their model generalizes well with other unseen datasets. To meet the requirement of a deeper network, the VGG16 model uses a repeated set of convolutions, ReLu, and pooling layer. To overcome the drawback of AlexNet, an extended version of VGG16 architecture was developed in VGG19 to improve the overall accuracy of the system.

Mehta et. al. developed three light-weight CNN models and ensemble them. They found that their associated accuracy is more than the individual models [25]. They extracted the features through several lightweight CNN models with minimum pre-processing. Their proposed model was assessed on ear images of the IITD-II dataset, and they reported over 98% accuracy. In another work, they recently explored the application of Vision Transformers (ViTs) in computer vision tasks and developed a powerful model that combines CNNs and self-attention for 2D ear detection [26]. Their model worked on the ear dataset in worldwide representation. The model performance is validated across two challenging datasets of Kaggle and IITD-II in which experimental results show an accuracy of 99.36% and 91.25% respectively with a 16×16 patch size.

Rastogi et. al presented an ear biometric system for person identification with the help of only 60 ear images of the AMI dataset and reported an accuracy of 80% [27]. Their model was found to be rotation and scale invariant. Zhang and Mu applied Faster-RCNN methods to locate the correct ear portion from side profile images and discard the false positives automatically [28]. This model was validated on the UND-J2 ear image dataset, which is a challenging dataset containing variations in pose, occlusion, and illumination. They reported 100% and 98.22% accuracy on UND-J2 and UBEAE ear image datasets, respectively.

Mehta et al. applied deep learning techniques on smaller ear image datasets and overcame the limitations of a small dataset through an augmentation technique [29]. They validated their experiments on both constrained and unconstrained image datasets and achieved very good results. Transfer learning for computer vision tasks such as text classifications [30], link prediction [31], disease classification [32], rank learning [33], and sentimental classifications [34] have been widely reported in the literature. Zarachoff et al. presented a 2D Wavelet-based Multi-Band PCA technique to perform ear recognition and achieved 94.14% accuracy [36]. Their approach outperforms the other PCA and eigenface methods.

Alshazly et. al presented an ear recognition model by constructing a Deep Residual Network(ResNet) of different depths [39]. They solved the problem of the limited dataset using three steps. In the first step, features are extracted using ResNet architecture. In the second step, they fine-tuned the pre-trained model on each dataset. In the third step, they fed the output of the fine-tuned model to the SVM classifier to perform classification tasks. They achieved recognition accuracy of 99.64%, 81.89% and 67.25% on three benchmark datasets AMI, WPUT, and AWE respectively. Susan et. al highlighted an important fact that yaw pose angles and various ear image distortions affect the recognition performance of deep learning-based ear recognition models [41]. In their study, they applied different variations of blurriness, additive noise, brightness, and contrast to see the effect of recognition performances.

Priyadharshini et al. in [43] introduced a six-layer deep convolutional neural network (CNN) architecture for ear recognition. They conducted experiments using the IITD-II ear dataset and the AMI ear dataset. Remarkably, the deep network model achieved a recognition rate of 97.36% for the IITD-II dataset and 96.99% for the AMI dataset. Furthermore, the robustness of their proposed system was validated in an uncontrolled environment using the AMI Ear dataset.

Meromania et al. in [46] reported an efficient online personal identification system based on ear images. Their identification algorithm focuses on extracting a specific set of features for each ear. These features are derived from the Gabor filter response and include phase, module, and a combination of the real and imaginary parts. By testing various feature combinations during the fusion phase, they achieved an optimal multi-representation system, resulting in improved identification accuracy. They reported a Rank-One Recognition (ROR) rate of 90.21%, with the lowest Rank of Perfect Recognition (RPR) at 154.

In their study, Ramos-Cooper and Camara-Chavez introduced a novel dataset, meticulously crafted from the VGGFace dataset [47]. They fine-tuned pre-trained deep models and meticulously analyzed their responsiveness to various data covariates. Additionally, they delved into score-level fusion techniques to enhance overall recognition performance. Their experiments encompassed both open-set and close-set scenarios, utilizing the proposed dataset alongside the challenging UERC dataset. Notably, they achieved a remarkable 9% improvement by employing a pre-trained face model compared to a general image recognition model. Furthermore, fusing scores from both models yielded an additional 4% performance boost.

Recently, Sowmya and Prasanna presented a Gannet Sparrow Search Optimization enabled Convolutional Neural Network with Transfer Learning(GSSO_CNN-TL) for recognizing a person using their ear images [48]. This approach achieves more than 95% accuracy on the ear dataset downloaded from Kaggle. A compilation of articles employing deep learning for ear recognition tasks is presented in Table 1

In this paper, an ensemble approach combines two distinct CNN models VGG16 and VGG19 for feature extraction, aiming to enhance the classification accuracy of the ear recognition model. The experimental results highlight their advantages over existing methods.

TABLE 1. Overview of existing ear recognition techniques and their performance on different databases.

Technique	Used method	Used Dataset	Accuracy (%)
Ear Recognition Based on Deep Unsupervised Active Learning [6]	Supervised learning and Unsupervised active learning	USTB-II AMI AWE	100 98.33 51.25
Ear recognition based on SSD-MobileNet-v1 network [7]	SSD-MobileNet-v1 deep learning	USTB	99.98
Ear recognition using deep CNN [9]	Handcrafted features using neural networks	UND USTB IITD	98.22 95.73 96.13
Deep CNN for unconstrained ear recognition [10]	Domain adaptation with transfer learning	EarVN1.0	95.85
Ear recognition using six convolutional layers [43]	Deep convolutional layer with different optimizers	AMI IITD-II	96.99 97.36
Ear identification using Gabor filter responses [46]	Based on Gabor filters response for feature extraction and Hamming distance for matching purposes	IITD-II	92.39
Deep CNN using data augmentation [29]	Augmentation and deep CNN	AMI IITD-II AWE	98.57 95.98 86.10
Ear recognition using deep ensemble learning approach [25]	Average and weighted average ensemble technique	IITD-II	98.74
Domain adaption for unconstrained ear recognition [47]	Fine-tuning strategies of deep pre-trained mode	UERC	71.0

III. MATERIALS AND METHODOLOGY

In this section, two datasets, Kaggle and IITD-II, are introduced. It then delves into the architecture of the VGG16 and VGG19 models, providing detailed insights. The ensemble technique combines these two models, serving as a hybrid transfer learning approach. Instead of relying on a fully connected layer, an SVM classifier aids in performing the classification tasks. Lastly, each of the proposed models undergoes fine-tuning based on problem suitability. To give a detailed description of the materials and methodology of the proposed model, this section is divided into six subsections as follows:

A. DATASET DESCRIPTIONS

1) KAGGLE DATASET

The proposed models were initially applied to an ear dataset obtained from Kaggle [35]. This dataset comprises 2,600 images representing 13 distinct subjects. All images within the dataset have dimensions of 227 × 227. During pre-processing, the images were resized to 150 × 150 to match the input size required by the CNN in the hybrid model. The dataset includes both color and grayscale images. Figure 1 displays a sample of ear images from this dataset. The dataset was divided into training and test sets, maintaining a 9:1 ratio, where 2,360 images were used for training, while 240 images served as the test dataset.

2) IITD-II DATASET

The IIT Delhi-II ear image dataset comprises ear images captured under consistent environmental conditions [49]. This dataset is intentionally limited in scope and consists of a total of 793 labeled images representing 221 distinct individuals. After dividing the dataset in an 8:2 ratio,

FIGURE 1. A selection of ear images from the Kaggle dataset [35].

634 images were allocated for training, while 159 images were reserved for the test set. All images share a uniform resolution of 50 × 180. Figure 2 displays a selection of sample images from this dataset.

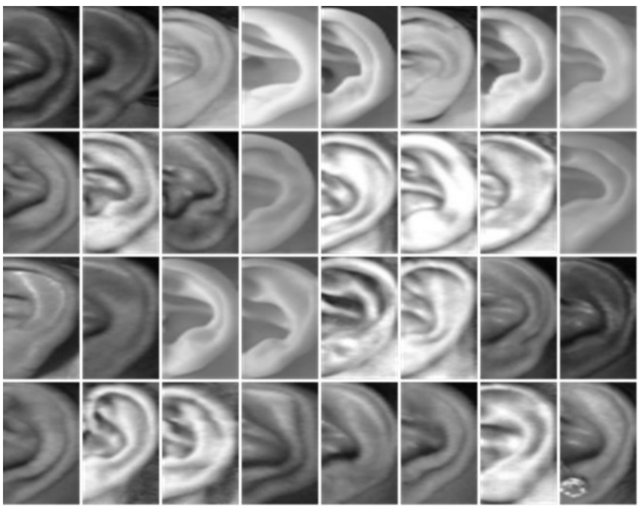


FIGURE 2. A selection of ear images from the IITD-II ear dataset captured under controlled environmental conditions [49].

B. PROPOSED ENSEMBLE-BASED HYBRID TRANSFER LEARNING MODEL

The proposed ensemble-based hybrid transfer learning approach combines the strength of ensemble learning and transfer learning to improve the recognition accuracy of the system. We utilize the concept of transfer learning using two popular CNN models, VGG16 and VGG19, which are already trained on the ImageNet dataset. This approach saves the model's training time. Here, we only perform a fine-tuning strategy so that it operates well on the used two-ear image datasets. Different layers of the VGG16 and VGG19 models help with the extraction of different features from the input images. For example, their early layers, $conv1\_1$, $conv1\_2$, extract basic edges and color gradients present in the ear images, while the intermediate layers are responsible for extracting complex patterns and connected parts of the ear portions. Thus, more semantic information, such as connected components of edge-of-the-ear images, is extracted in the intermediate layers. These features are extracted by combining the basic features detected in the early layers of the models. The deeper layers of the VGG16 and VGG19 models extract more abstract and high-level features like the shape of the ear and other minute details present in the ear images. These features are less spatially detailed and are generally not captured in the early layers. Hence, diverse feature distributions are easily handled, controlled, and transferred from one domain to another, accelerating the learning process with improved generalizations. Some sample features and characteristics of the ear images extracted by the VGG16 and VGG19 models are illustrated in Figure 3

Instead of using a fully connected layer, we utilize an SVM classifier to perform the classification task. Each pre-trained model generates a probabilistic-based output. The average of the resulting probabilistic is used to generate the final output. The entire process that combines the two hybrid transfer learning models into an ensemble model is illustrated in Figure 4.

C. ENSEMBLE OF VGG16 MODEL WITH SVM

The architecture of the first deep learning model, comprising VGG16 and the SVM classifier, is illustrated in Figure 3. The model is fine-tuned according to the suitability of the problem. The fully connected layer of the VGG16 model was replaced with the SVM classifier. In this stage, two tasks are mainly performed. In the first task, the first 13 convolution layers of VGG16 extract robust and intrinsic features from the input ear images. The classification task is performed in the second stage using the SVM classifier. Hence, the last three layers of the VGG16 model were replaced with a dense layer consisting of 128 and 13 neurons. The input ear image is convolved using several convolutional layers and max pooling layers, as shown in Figure 5.

The combination of the convolution and max pooling layers increases the network's efficiency by reducing the spatial dimensionality of the feature maps. The obtained feature maps are then flattened into one-dimensional vectors. These vectors are fed to the SVM layer. Based on the features extracted from the convolutional layers of the VGG16 model, the SVM performs the classification, thereby leveraging the representation power of the VGG16 model and classification capabilities of the SVM. This capability makes the system invariant to pose, illumination, occlusion, and rotations. Thus, the proposed hybrid transfer learning approach combines the capability of transfer learning and fine-tuning, allowing ear-based classification with higher accuracy, faster convergence, and improved generalization.

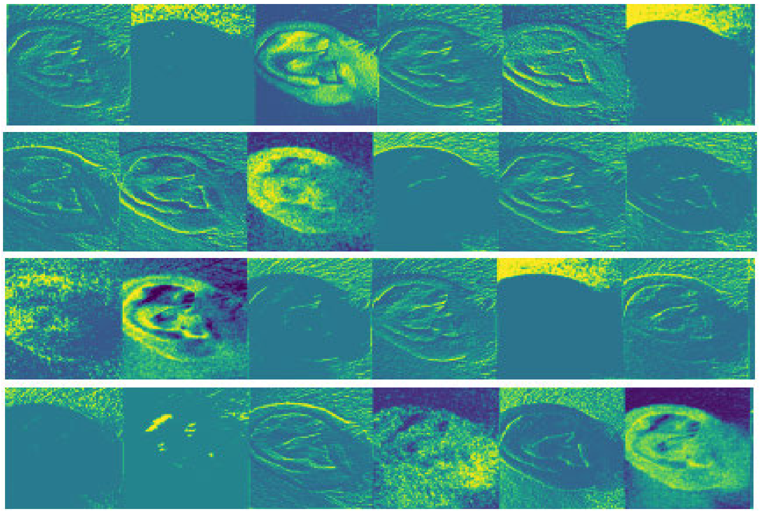


FIGURE 3. Sample extracted features characteristic from an ear image by VGG16 and VGG19 models.

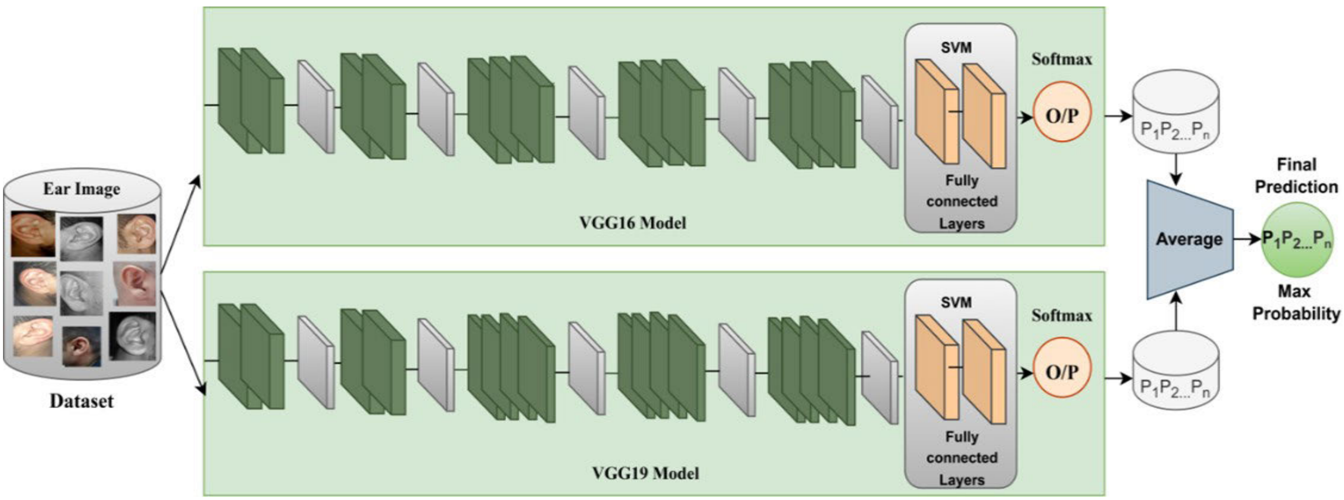


FIGURE 4. The proposed ensemble method using hybrid transfer learning model.

D. ENSEMBLE OF VGG19 MODEL WITH SVM

The architecture of the proposed ensemble model using VGG19 and SVM is illustrated in Figure 6. Like the ensemble model using VGG16 and SVM, the VGG19 model is fine-tuned according to the problem-specific tasks, and its last layer uses the SVM classifier to classify the ear images. In this stage, the first 16 convolution layers of the VGG19 are used for feature extraction, whereas the SVM performs the role of a fully connected layer to do the classification. Hence, the last three layers of the VGG19 model are replaced with a dense layer consisting of 128 and 13 neurons, respectively.

E. MODEL TUNING

In this section, we explore concise descriptions of fine-tuning strategies on two popular CNN models, VGG16 and VGG19. With this strategy, these models enhance both training efficiency and accuracy when dealing with challenging ear image datasets [35], [49]. In the fine-tuning stage, we retain the first 13 layers from VGG16 and the 16 layers from the VGG19 network as fixed components. The last three layers of each network are replaced with a fully connected layer containing 128 and 13 neurons for classification. To solve the problem of non-linearity, the Rectified Linear Unit (ReLu) activation function is added to the last layer of each network. This function speeds up the training procedure and makes the model free from the vanishing gradient problem. To validate the proposed method, we execute each model for a different number of epochs on two datasets. Before training the model, each dataset is partitioned into training and test sets in different ratios. Details regarding the number of images in the training and test sets, as well as the number of runs for each model, are provided in Table 2. For every model, we set

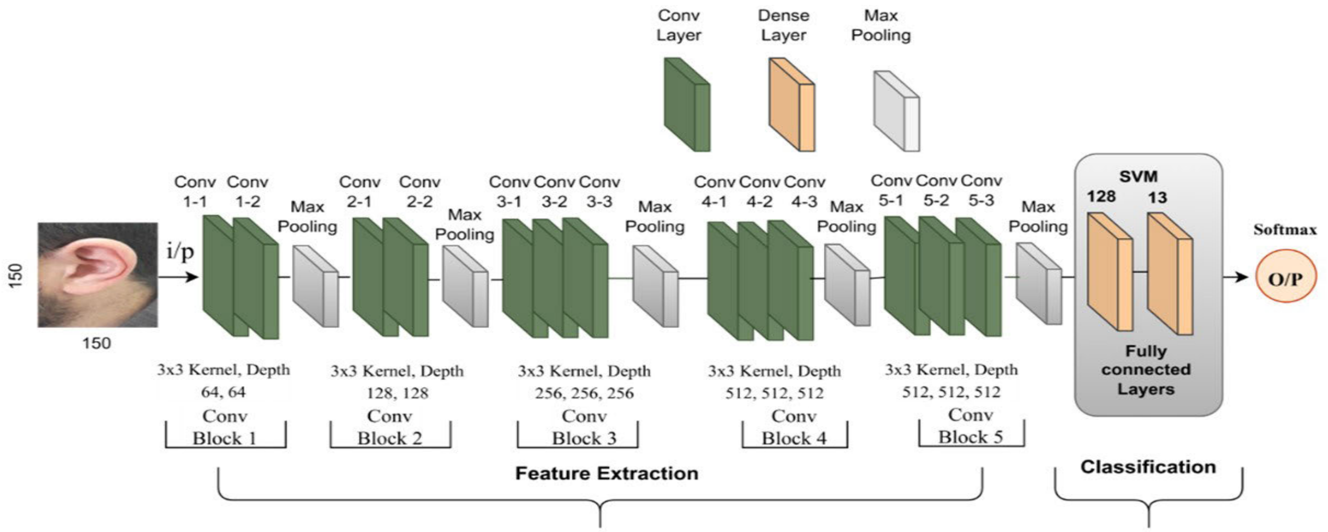


FIGURE 5. Block diagram of the proposed ensemble model using VGG16 and SVM.

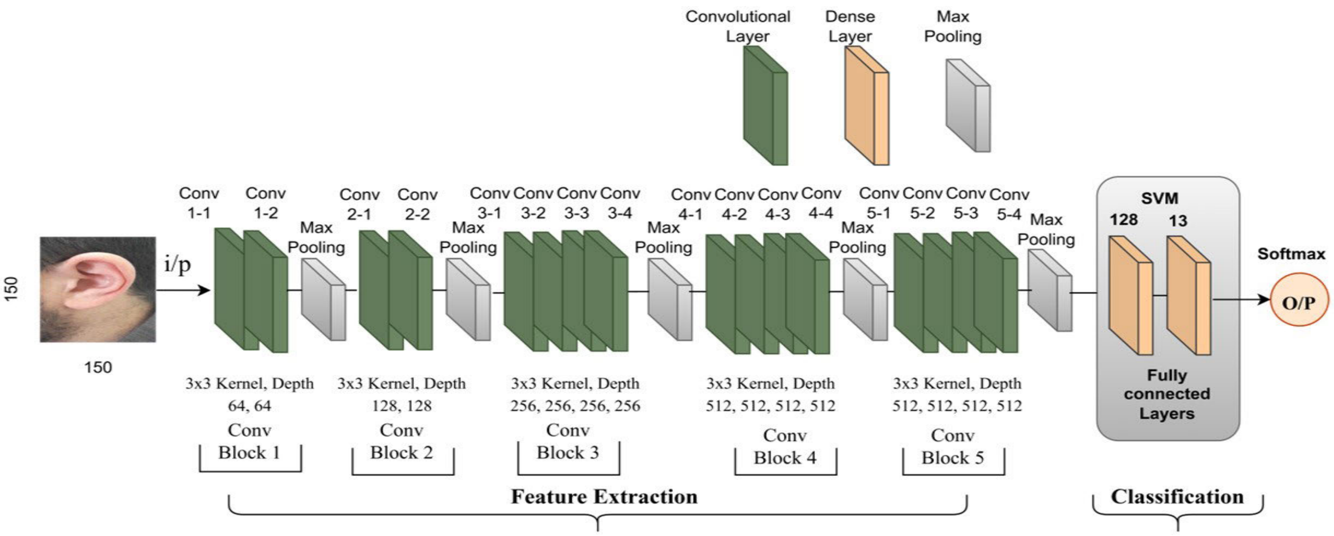


FIGURE 6. Block diagram of the proposed ensemble model using VGG19 and SVM.

the learning rate to 0.001 and the batch size to 16. To perform the classification tasks with the SVM classifier, the squared hinge loss function was used.

F. IMPLEMENTATION STEPS

In this section, a concise explanation of the implementation steps undertaken to construct the proposed model is presented. The model was executed on a 3.40 GHz Core i9 processor with 16 GB of RAM, utilizing Python version 3.7.8.

Step 1: Pre-processing

a) The input images are resized to a fixed size (150 × 150) to facilitate convolution.

b) The dataset is split into training and test datasets.

Step 2: Model Training

a) The pre-trained model is independently fine-tuned, considering the number of classes present in the datasets.

b) Various hyperparameters, including loss functions, optimizers, number of epochs, learning rate, iterations, batch size, and dropout, are configured.

c) Step b is repeated for both pre-trained models.

Step 3: Ensemble of Models

a) After training each pre-trained model, a predicted output using an SVM classifier is obtained. The reason for using SVM is mainly due to its interpretability. The decision boundary in SVM is determined by a subset of training data called support vectors, which helps in identifying the critical features for classification. Additionally, SVM classifiers generalize well even with relatively small datasets and are less prone to overfitting compared to deep neural network

TABLE 2. Training parameter of each used CNN Model in the ensemble technique.

Dataset	Model	Epochs	Loss function	Optimizers	Batch Size	Training Set	Test Set	Learning Rate
Kaggle	Model1 (VGG16+SVM)	30	squared hinge	Adam Optimizer	16	2340	260	0.001
	Model2 (VGG19+SVM)	30	squared hinge	Adam Optimizer	16	2340	260	0.001
IITD-II	Model1 (VGG16+SVM)	100	squared hinge	Adam Optimizer	16	634	159	0.001
	Model2 (VGG19+SVM)	100	squared hinge	Adam Optimizer	16	634	159	0.001

methods. In the proposed method, the two datasets used have small sizes in terms of the number of images. Therefore, the application of SVM helps mitigate the overfitting problem.

b) The predicted outputs of the two models are then combined using their average and weighted average to generate the ensemble model's output.

IV. RESULTS AND DISCUSSIONS

To evaluate the performance of the proposed methods, experiments were conducted using images from the Kaggle and IITD-II datasets. The dataset was split into training and test sets in a ratio of 9:1 for Kaggle and 8:2 for the IITD-II dataset. For the training procedure, a system with 16 GB of RAM and a simple CPU running at a speed of 3.70 GHz was used. The proposed method was implemented using Python IDLE (version 3.7.8) and built upon the TensorFlow framework. The ear images in the Kaggle dataset have a resolution of 227×227, while the two CNN models used accept images with a resolution of 150×150. Therefore, the input images were first resized to 150×150. This step was followed for both datasets, as the image resolutions varied across them. To learn specific patterns, the top layers of both the VGG16 and VGG19 models were fine-tuned. The experiments were conducted using the hyper-parameters tabulated in Table 3.

TABLE 3. Hyper-parameters used for both models.

Hyper Parameters	Values
Image size	150 x 150
No. of epochs	30/100
Batch Size	16
Batch Size	16
Filter Size	3 × 3
Dropout	0.5
Learning iterations	10
Learning Rate	0.001
Regularizations	L2 = 0.01
Loss functions	squared hinge
Optimizers	Adam

The model is executed for 30 and 100 epochs on two different datasets, namely Kaggle and IITD-II, respectively. To apply the SVM classifier for classification purposes, we utilize squared hinge functions during model training. For the entire dataset, we set the batch size equal to 16. In convolution operations, a filter of size 3×3 is used. The Adam optimizer tunes the network parameters, preventing overfitting issues and optimizing the loss function. Sparse gradients pose a significant challenge in noisy environments, but this optimizer effectively addresses these issues. Ridge regularization (L2) with a value of 0.01 is applied in the last dense layer. The L2 regularization controls the strength of the penalty on the square value of the model's weights. Calculating the ideal regularizer value is challenging, as a larger value heavily penalizes the model due to higher weights, reducing the risk of overfitting due to the small training data size. Conversely, using a lower value makes the models more complex and more prone to overfitting the training set. The squared hinge loss function at the last layer of the model enables classification through an SVM classifier. Additionally, the SoftMax activation function at the last layer of each model provides probabilistic output to classify input images into different classes based on the number of distinct subjects present in the dataset. For each model, this SoftMax activation function yields probabilistic-based outputs, which are then averaged to create the final prediction.

To evaluate the contributions of each model in the ensemble-based approach, we calculate the accuracy of each model individually and their combined accuracy using ensemble techniques. These results are tabulated in Table 4. Additionally, other performance metrics such as Precision, Recall, F1_score, and Accuracy for each model individually and in combination are also presented in Table 4.

From Table 4, the combination utilizes 60% weights from the VGG16 model and 40% weights from the VGG19 model, resulting in an accuracy of 100%. Additionally, at this stage, the precision, recall, and F1_score metrics also achieve their highest accuracy of 100%.

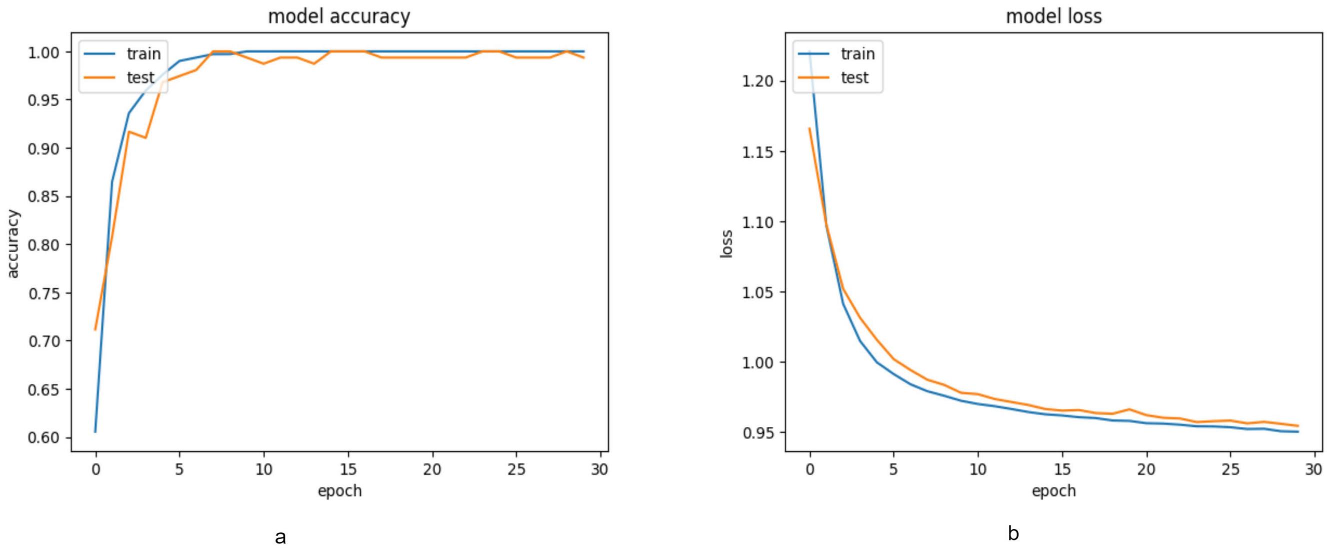


FIGURE 7. (a) Model accuracy and (b) Model loss of VGG16 and SVM classifier on the Kaggle dataset.

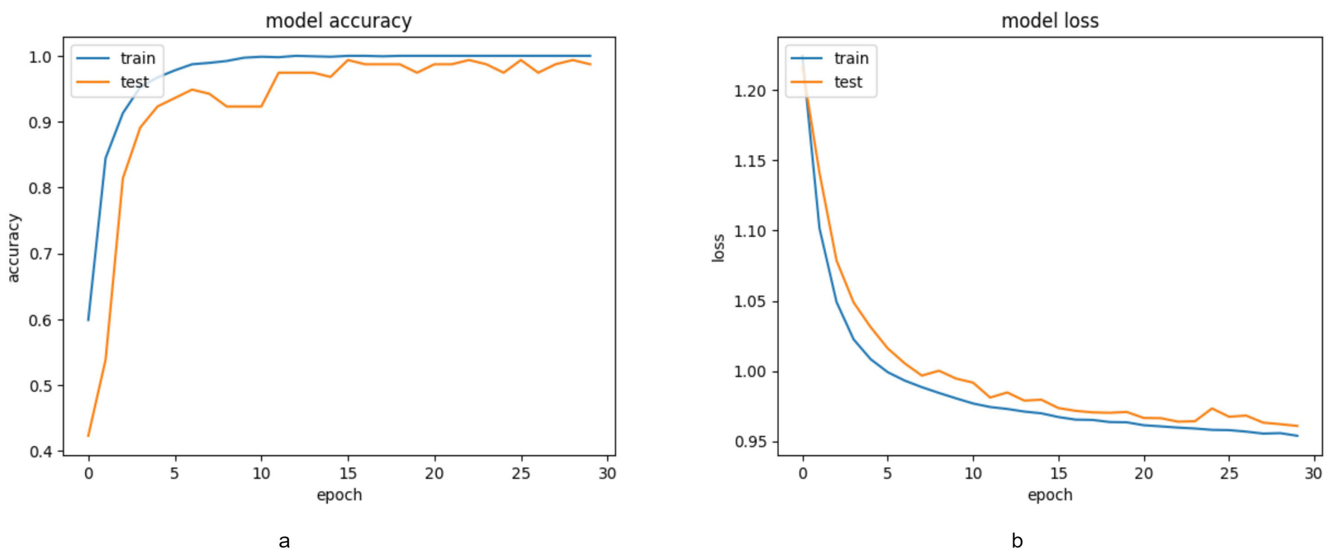


FIGURE 8. (a) Model accuracy and (b) Model loss of VGG19 and SVM classifier on the Kaggle dataset.

TABLE 4. Performance of the proposed ensemble method using different combinations of the two CNN models on the Kaggle dataset.

	VGG16 (ACCURACY OF 0.9935)	VGG19 (ACCURACY OF 0.9871)	ENSEMBLE ACCURACY	PRECISION (%)	RECALL (%)	F1_Score (%)
W1	0.3	0.7	99.35	99.43	99.35	99.36
W2	0.8	0.2	99.48	99.40	99.35	99.36
W*	0.6	0.4	100.0	100.0	100.0	100.0

To demonstrate the efficiency of the proposed model compared to other existing models, we also validated the results using the IITD-II ear dataset. For the performance evaluation of each model, we plotted accuracy and loss against epochs for each model, as shown in Figures 8 and 9. It has been observed that on the IITD-II dataset, the

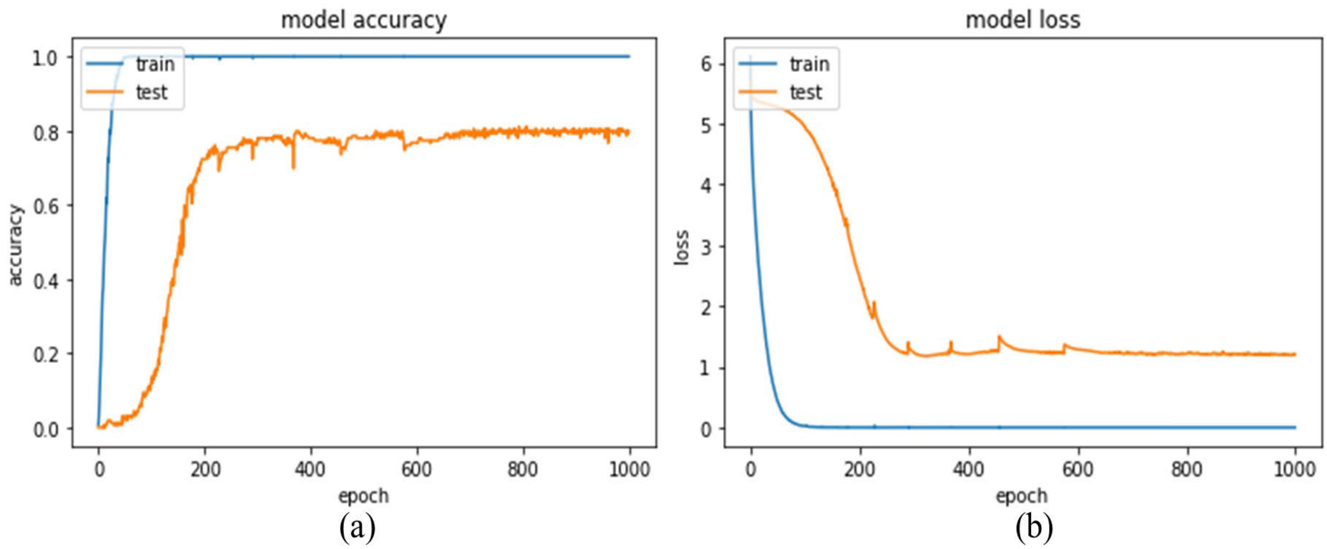


FIGURE 9. **(a) Model accuracy and (b) Model loss of VGG16 and SVM classifier on the on IITD-II dataset.**

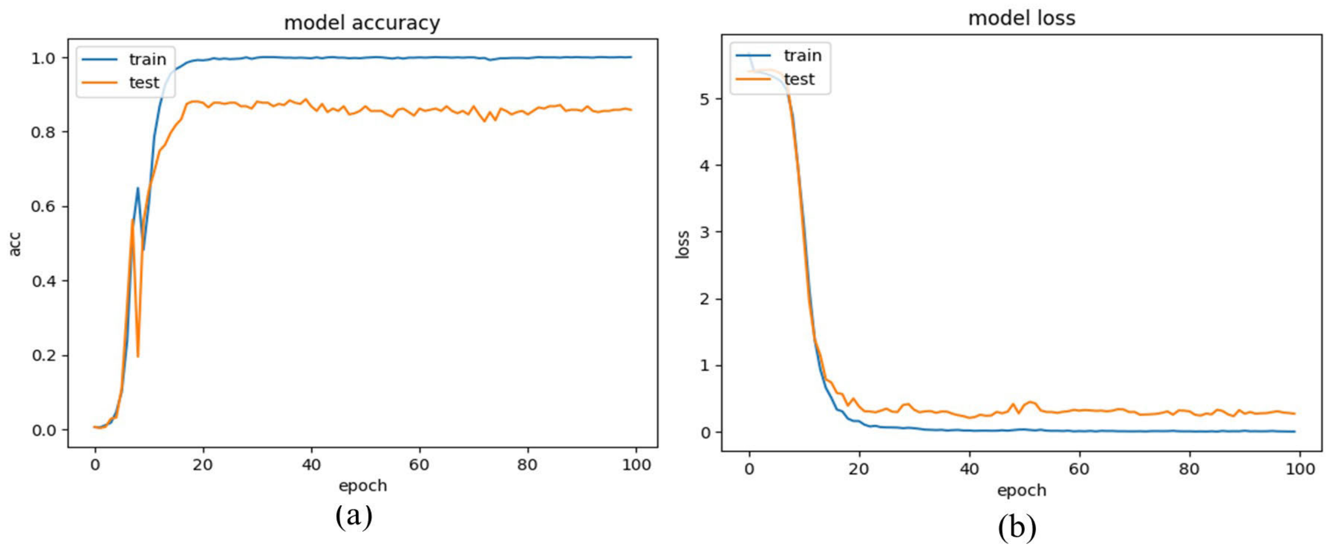


FIGURE 10. **(a) Model accuracy and (b) Model loss of VGG19 and SVM classifier on the on IITD-II dataset.**

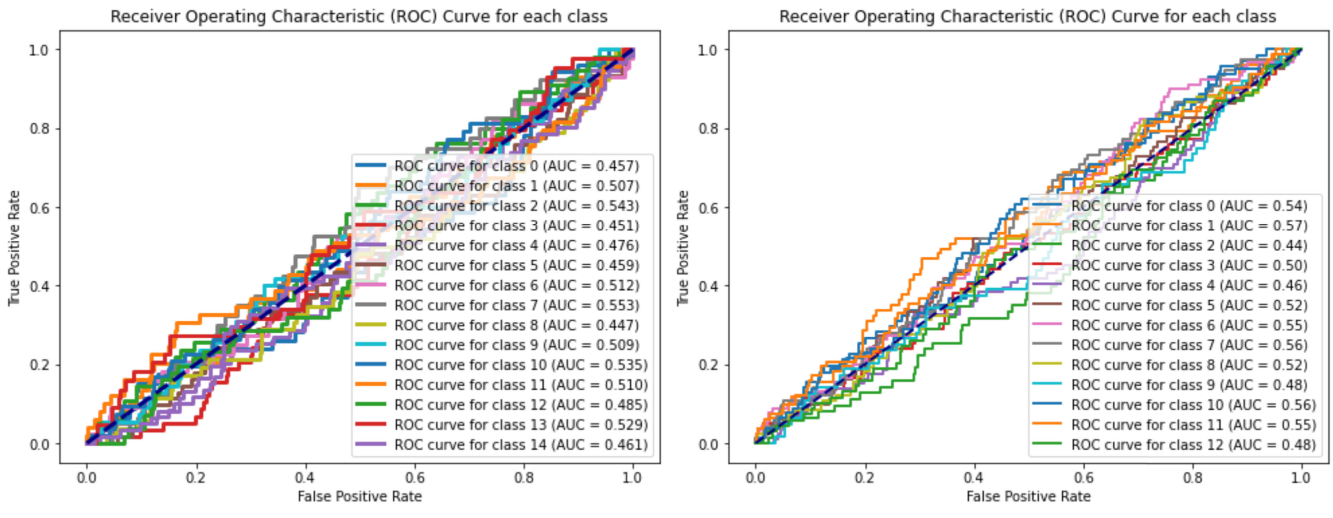
VGG16 model with an SVM classifier converges after just 200 epochs, achieving a maximum model accuracy of 83.17%. Additionally, the VGG19 model with an SVM classifier achieves a model accuracy of 91.78%. Using a learning rate of 0.001 and a batch size of 16, the VGG19 model converges after only 25 epochs.

To assess the impact of each model within the ensemble-based approach on the IITD-II dataset, we compute the individual accuracy of each model as well as their combined accuracy using ensemble techniques. These findings are summarized in Table 5. Furthermore, Table 5 includes additional performance metrics such as Precision, Recall, F1-score, and Accuracy for both individual models and their combined configurations.

To evaluate the performance of the proposed model, we employed a weighted average ensemble technique. From Table 5, it is evident that the VGG19 model outperforms the VGG16 model in terms of accuracy. We assigned random weights to these two models, ranging from 0.1 to 0.9. The accuracy plot, generated by varying the model ratio between 8:2 and vice versa, is presented in Table 5. Notably when we combined 70% accuracy from the VGG19 model with 30% accuracy from the VGG16 model on the IITD-II dataset, we achieved a maximum accuracy of 93.47%. Due to lower variability in the IITD-II dataset compared to the Kaggle dataset, the accuracy with IITD-II is relatively lower. Additionally, we plotted the AUC curve in Figures 10(a) and 10(b) for both datasets to demonstrate

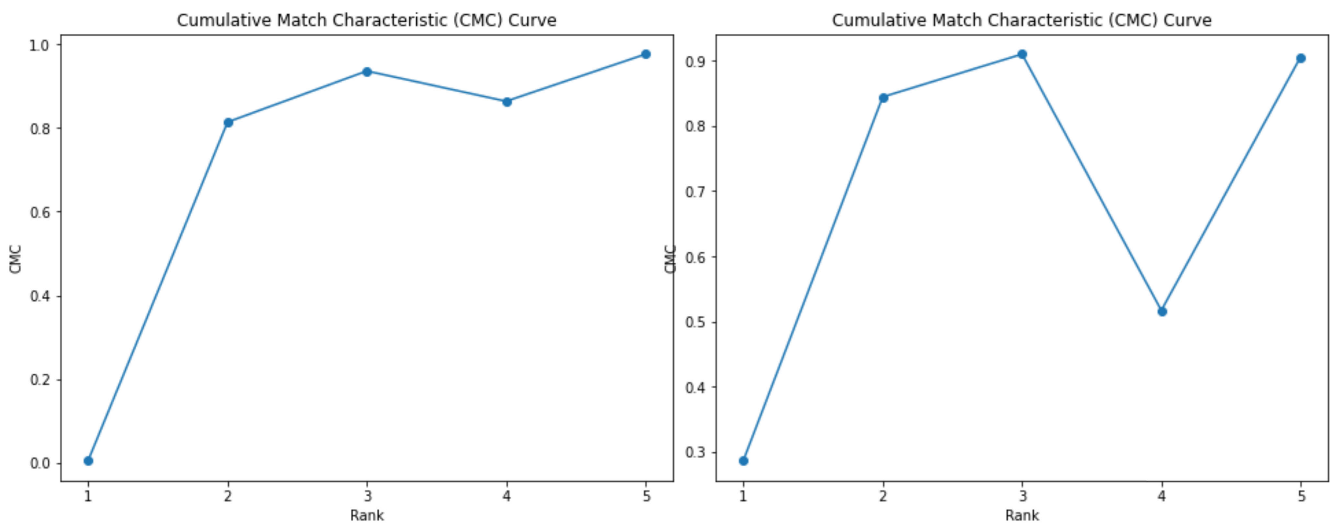
TABLE 5. Performance of the proposed ensemble method using different combinations of the two CNN models on the IITD-II dataset.

	VGG16 (ACCURACY: 83.17%))	VGG19 (ACCURACY: (91.35%)	ENSEMBLE ACCURACY (%)	PRECISION (%)	RECALL (%)	F1_Score (%)
W1	0.2	0.8	92.71	92.11	92.36	92.23
W2	0.8	0.2	92.18	92.21	92.08	92.14
W*	0.3	0.7	93.47	93.67	93.29	93.57



a b

FIGURE 11. AUC curve of the proposed ensemble method on (a) the Kaggle dataset and (b) the IITD-II dataset.



a b

FIGURE 12. CMC curve for the proposed ensemble method on (a) Kaggle dataset (b) IITD-II dataset.

recognition efficiency. Remarkably, our ensemble-based hybrid transfer learning approach consistently outperformed normal cases. However, due to the uneven distribution of images in the Kaggle/IITD-II dataset, some features could not be effectively retrieved by the model. The IITD-II dataset contains 221 classes, while the Kaggle dataset has

TABLE 6. Hyper-parameters used for both models.

Related Article	DATASET	Accuracy(%)
Image classification using Transfer learning (VGG16) [12], 2018	caltech256	88.04
Image classification using Transfer learning (VGG19) [12], 2018	caltech256	88.63
Image classification using Transfer learning (VGG16) [12], 2018	GHIM10k	98.57
Image classification using Transfer learning (VGG19) [12], 2018	GHIM10k	99.38
Single Image ear recognition using wavelet-based multi-band PCA [36], 2019	IITD-II	94.14
Ear recognition using Domain adaptation with VGG16 [40], 2018	Multi-PIE	98.57
Ear recognition using Domain adaptation with GoogleNet [40], 2018	Multi-PIE	97.80
Ear recognition with ensemble classifiers(AlexNet)) [37], 2019	IITD-II	94.29
Ear recognition with ensemble classifiers(GoogleNet)) [37], 2019	IITD-II	90.71
Ear recognition with ensemble classifiers(ResNet50)) [37], 2019	IITD-II	93.57
Deep Learning Models for Ear Recognition Against Image Distortions [41], 2019	UERC	98.33
Non-Decimated WBMBPCA for ear recognition [42], 2021	IITD-II	94.47
Deep learning model for person identification using ear biometrics [43], 2021	IITD-II	97.36
Ear recognition technique based on deep ensemble learning approach [25], 2023	IITD-II	98.74
Ear recognition using Gabor filters and ensemble of pre-trained deep CNN [45], 2023	AWE	74.63
Transfer Learning: Ear Biometric Recognition using CNN [44], 2022	IITD-II	88.37
Transfer Learning: Ear Biometric Recognition using VGG16 [44], 2022	IITD-II	88.73
Transfer Learning: Ear Biometric Recognition using ResNet50 [44], 2022	IITD-II	89.71
Ear recognition using hybrid transfer learning model with VGG16+SVM [13], 2023	Kaggle	98.72
Ear identification using Gabor filter responses [46], 2015	IITD-II	92.39,
Deep CNN using data augmentation [29], 2023	IITD-II	95.98
Proposed ensemble-based hybrid transfer learning model	IITD-II	93.57
Proposed ensemble-based hybrid transfer learning model	Kaggle	100.00

13 classes. We generated AUC curves using different colors corresponding to the number of classes in each dataset. Specifically, for the Kaggle dataset, we plotted the AUC curve for all 13 classes, as depicted in Figure 10(a). In contrast, for the IITD-II dataset, which has 221 classes, we focused on visual clarity and plotted the AUC curves for only 15 classes, as shown in Figure 10(b). This selection ensures that the curves remain distinct and easily interpretable without overlapping.

We have also plotted the CMC curve for two different datasets, as shown in Figures 11(a) and 11(b). The graph demonstrates that the ensemble model yields the best results with respect to R5, exceeding 98% on the Kaggle dataset. Simultaneously, the same model achieves the best results with respect to R5, exceeding 93% on the IITD-II dataset.

Furthermore, the proposed ensemble-based hybrid model outperforms other state-of-the-art methods, as indicated in Table 6.

V. CONCLUSION

In this paper, we aim to address the challenges posed by ear recognition which includes variations in illumination, rotations, and occlusion due to hair or earrings. For this purpose, we proposed an ensemble-based hybrid transfer learning approach that leverages the power of VGG16 and VGG19 models in conjunction with an SVM classifier.

To validate our approach, we conducted extensive experiments using two datasets comprising 2600 ear images from Kaggle and 793 images from the IITD-II dataset. These datasets exhibit significant variability, making them suitable for rigorous evaluation. To extract the distinct features two pre-trained models VGG16 and VGG19 models are used. The extracted features are then fed into the SVM classifier for classification tasks. The results demonstrate that our proposed ensemble model outperforms individual models.

Furthermore, our approach surpasses existing state-of-the-art methods. Looking ahead, we envision extending this ensemble-based hybrid transfer learning model to incorporate lightweight CNN architectures. By doing so, we can seamlessly integrate our solution into mobile devices for real-time applications, such as object recognition and human action identification. This research opens exciting avenues for improving ear recognition systems, emphasizing both accuracy and practical deployment in real-world scenarios.

Conflict of interest:

The authors declare that they have no conflict of interest.

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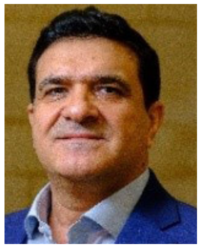

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