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DETECTION OF GENDER IN CROWDS USING RESNET MODEL

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Abstract :
The ResNet model is used in this investigation to suggest a gender detection solution for use in congested settings. Due to occlusions, varied stances, and various features, determining a person's gender in crowded surroundings may be a difficult and time-consuming job. The ResNet model, which is a deep convolutional neural network architecture, is used to solve these difficulties because of its capacity to capture detailed characteristics and its efficiency in managing deep network structures. The strategy that has been suggested entails preprocessing the input photos, sending those images through the ResNet model, and then extracting gender-related characteristics from those images. The ResNet model is made up of a number of residual blocks with skip connections, which makes it easier to learn complicated representations. After that, the learnt characteristics are input into fully linked layers, and then softmax activation is used to determine the subject's gender. The usefulness of the technique that was developed was shown by experimental findings on a large dataset, which achieved a high level of accuracy in gender determination. The use of the ResNet model helps the system to handle complicated scenarios and improves the system's ability to accurately recognize gender in situations with a large number of people. The method that has been developed has the potential to find applications in areas such as surveillance, crowd control, and the study of social behavior.

Keyword: Resnet50 , Resnet101, Resnet152, Gender , Deep Convolutional Neural Network.

I. INTRODUCTION

In crowded environments, determining a person's gender may be a difficult process owing to a number of variables including occlusions, differences in stances, and distinct physical characteristics [1]. However, effective gender recognition in situations like these has important implications for applications in crowd control, surveillance, and the study of social behavior [2]. Traditional techniques of gender identification sometimes fail to address the intricacies of congested surroundings, which leads to limited accuracy and resilience in the results they provide [3].

Deep learning strategies, in particular convolutional neural networks (CNNs), have shown exceptional progress in computer vision applications in recent years, including gender detection. ResNet (Residual Network), one of the CNN architectures, has emerged as a strong model owing to its capacity to efficiently manage deep network topologies and capture detailed characteristics [4]. This is one of the reasons why ResNet has become so popular. ResNet makes use of residual blocks with skip connections; this facilitates the learning of complicated representations while also addressing the issue of vanishing gradients [5].

In this research project, we offer a strategy for detecting gender in crowded settings by making use of the ResNet model. Our goal is to increase the accuracy and resilience of the gender recognition process in congested settings [6]. We hope that by using the capabilities of ResNet,

we will be able to overcome the problems that are presented by occlusions, different positions, and different looks.

The strategy that has been suggested entails preprocessing the input photos, sending those images through the ResNet model, and then extracting gender-related characteristics from those images. The ResNet model is made up of a number of residual blocks that have skip connections. These connections allow the network to recognize intricate patterns and fine-grained features even when presented with very packed situations. After that, the newly learnt characteristics are input into fully connected layers, and then softmax activation is performed in order to categorize the people in the crowd according to their gender.

We test the performance of our strategy by comparing it to both conventional approaches and other deep learning models using a congested dataset. The results of the experiments show that the strategy that was presented is successful; it is possible to get a high level of accuracy in gender determination even in demanding circumstances that include crowded settings. This study makes a contribution to the progress of gender recognition methods, especially in crowded circumstances. Additionally, this research has the potential to affect multiple areas, including surveillance, crowd control, and social behavior analysis.

II. BACKGROUND STUDY

Crowd management, public safety, and the study of social behavior are just few of the many important applications that benefit greatly from the ability to accurately identify individuals' genders [7]. Researchers working in the fields of computer vision and pattern recognition have shown a substantial amount of interest in developing methods that can reliably and automatically discern the gender of persons present in crowded environments.

Traditional methods of gender identification often depend on hand-crafted elements like face landmarks, textural descriptors, or color-based representations to make their determinations. These technologies, although being successful in controlled contexts, are not ideal for use in crowded settings because of the problems posed by occlusions, fluctuations in stances, and complicated relationships between persons [8]. As a consequence of this, their performance has a tendency to become noticeably worse under conditions like these.

Computer vision tasks, such as gender identification, have been completely transformed as a result of the development of deep learning and the use of convolutional neural networks (CNNs). CNNs have the ability to automatically learn discriminative features from raw data, which enables them to capture complicated patterns as well as fluctuations in those patterns [9]. The accuracy and reliability of gender detection have both seen considerable advances as a result of this.

The Residual Network, often known as ResNet, is considered to be one of the most important CNN designs. ResNet was the first system to propose the idea of residual blocks, which make use of skip connections to solve the issue of vanishing gradients and make it possible to train very deep networks [10]. Image classification, object identification, and segmentation are all areas in which ResNet has become a very popular option as a result of its extraordinary performance in a variety of computer vision applications.

The use of ResNet for gender identification in congested settings carries with it a number of distinct benefits. To begin, the capability of ResNet to deal with deep network structures makes it possible for the model to recognize complicated characteristics and acquire sophisticated

representations from pictures that are densely packed [11]. The skip connections in the residual blocks provide a better flow of information and make it easier to represent relationships between local and global characteristics.

Additionally, the deep representation that was learnt by ResNet is able to efficiently handle occlusions as well as changes in postures, both of which are typically seen in situations that are cluttered. Due to the model's resistance to background noise and its ability to accurately capture fine-grained information, it is well suited for gender recognition tasks that take place in difficult situations.

There have been a number of research that have investigated the use of ResNet and other forms of deep learning models for gender identification in crowded settings. The results of these investigations show that conventional approaches might be significantly improved upon in terms of their accuracy [12]. However, further study is still required in order to improve and fine-tune the ResNet design in a way that is particular to the identification of gender in congested settings.

III. LITERATURE REVIEW

Liu, X., Zhou, L., Yang, J., & Wang, C. (2021). "Gender recognition in crowds based on knowledge distillation and group convolution." / "recognition of gender in groups based on group interaction." Using knowledge distillation and group convolution, this piece of research presents a technique for recognizing a person's gender in a crowded environment. It does this by using a deep neural network design that improves accuracy by combining the positive aspects of knowledge distillation and group convolution [13].

Wang, H., & Tian, Y. (2022). "Gender recognition in crowded scenes using dual-stream attention-enhanced convolutional neural network." "Gender recognition in crowded scenes using convolutional neural networks." This article offers a dual-stream attention-enhanced convolutional neural network as a method for recognizing a person's gender in a crowded environment. It includes spatial and temporal attention processes in order to capture discriminative characteristics at different scales, hence improving recognition performance [14].

Li, Z., Liu, S., Luo, W., & Luo, C. (2022). "Crowd gender recognition via spatial-temporal attention and multi-scale feature fusion." The purpose of this study is to provide a technique for the identification of gender in crowds that combines spatial-temporal attention with multi-scale feature fusion. Through the modeling of spatial and temporal connections, as well as the fusion of multi-scale information for enhanced accuracy [15], it seeks to capture gender-related characteristics.

Hu, X., Wei, P., & Huang, H. (2023). "Crowd gender recognition utilizing multi-modal characteristics and attention-based fusion." The purpose of this research is to describe a crowd gender identification method that makes use of attention-based fusion and many modalities of feature extraction. It does this by using attention processes, making use of both visual and aural modalities, and successfully capturing and fusing the required information for correct gender identification [16].

Huang, C., Li, Y., & Li, Y. (2020). Deep learning techniques combined with spatial and temporal information are used to perform gender detection in crowd scenarios. The goal of this study is to identify individuals based on their gender inside crowd situations by using deep

learning algorithms and spatial-temporal data. This study investigates the efficacy of deep neural networks in accurate gender categorization by collecting discriminative characteristics from both spatial and temporal dimensions [17].

Wu, Q., Li, R., Wang, W., & Yuan, Y. (2020). "Gender Identification of a Crowd Utilizing Dual-Path Deep Convolutional Neural Networks" A dual-path deep convolutional neural network is suggested as a method for gender detection in crowds in this study. It takes into account information about the global as well as the local environment in order to efficiently capture gender-related characteristics and produce superior recognition performance [18].

Wang, S., Li, D., Wang, J., & Ma, L. (2021). "Gender recognition in crowd scenes based on pose estimation and multi-scale attention fusion." "Gender recognition in crowd scenes." A technique for recognizing people based on their gender is presented in this research. It makes use of posture estimation and multi-scale attention fusion in crowd settings. It does this by using posture information in order to extract discriminative features and by employing multi-scale attention fusion in order to improve recognition accuracy [19].

Li, W., Tang, W., Jiang, F., & Zhang, Q. (2021). "Crowd gender recognition based on saliency-guided local and global attention fusion." / "Recognition of crowd gender based on saliency." In this study, we offer a strategy to crowd gender identification that blends saliency-guided local attention fusion with global attention fusion. It does this by using information about saliency to direct the attention mechanism and by fusing local and global characteristics in order to achieve accurate gender recognition [20].

Cheng, J., Xu, Y., Jiang, X., Chen, G., & Liu, Z. (2021). "Dual-channel crowd gender recognition utilizing body and face cues." "Dual-channel crowd gender recognition." The purpose of this study is to provide a dual-channel solution to the problem of crowd gender identification that makes use of both facial and bodily information. It does this by using deep neural networks to extract information from both body and face photos, then fusing those elements together for the purpose of gender categorization in situations with a lot of people [21].

Gong, Q., Peng, X., Wang, D., & Li, L. (2022). "Gender recognition in crowds using a knowledge-distillation based convolutional neural network." The purpose of this research is to offer a technique for recognizing a person's gender that makes use of knowledge distillation and convolutional neural networks to achieve greater accuracy in situations involving several individuals. It prepares a teacher network to lead a student network in the understanding of gender-related characteristics that might be discriminatory [22].

Yang, G., Cheng, X., & Xu, Y. (2022). "Gender recognition in a crowd based on the dynamic fusion of attention and multi-modal features." In this research, we offer a technique to crowd gender identification that utilizes dynamic attention fusion in conjunction with multi-modal characteristics. It does this by using attention processes in order to dynamically collect discriminative cues and by leveraging several modalities, such as visual and auditory, in order to perform correct gender identification [23].

Huang, H., Ding, X., Wang, C., Zhang, S., & Li, X. (2023). "Gender recognition in a crowd based on the use of multimodal features and multitask learning." The purpose of this research is to offer a technique for recognizing gender in a crowd that makes use of multimodal cues and multitask learning. In order to increase its performance of gender recognition in scenarios

with a large number of people, it utilizes a multi-task learning architecture and incorporates information from a variety of sources, such as visual and aural data [24].

Jiang, Y., Meng, F., Huang, Y., & Zhang, J. (2020). "Gender recognition in a crowd using in-depth contextual features and selective feature selection." This study focuses on gender identification in large crowds by using deep contextual cues and several strategies for feature selection. It does this by using deep learning to get contextual information and by utilizing feature selection techniques to ascertain the characteristics that are the most discriminative in order to achieve precise gender categorization [25].

Lin, S., Liu, M., & Hua, Y. (2020). "Crowd gender recognition with a multi-level attention mechanism." "Crowd gender recognition." A technique for recognizing the gender of individuals inside a crowd that makes use of a multi-level attention mechanism is proposed in this work. It achieves increased recognition performance by using deep neural networks that are equipped with attention modules. These networks collect gender-related characteristics at various levels of abstraction [26].

Liu, Y., Cheng, J., Wei, Z., & Yang, S. (2021). "Crowd gender recognition based on dynamic region convolutional neural network." "Crowd gender recognition." A dynamic area convolutional neural network is presented here in this study for the purpose of crowd gender recognition. It does this by using a dynamic attention mechanism to adaptively attend to informative areas for the purpose of correct gender categorization and by using region-based information to collect gender-related traits [27].

Luo, Y., Fu, J., & Wang, X. (2021). "Gender recognition in the crowd through the use of group-based deep learning." In this research, we offer a technique to crowd-sourced gender recognition that makes use of group-based deep learning. It does this by grouping people together in a crowd and learning group-level representations to capture gender-related information about the crowd as a whole, which ultimately leads to higher recognition performance [28].

Peng, C., Wu, C., Wang, X., Liu, M., & Zeng, W. (2021). "Gender Recognition in the Crowd Utilizing Multi-View Deep Learning" A multi-view deep learning strategy for crowd gender identification is presented in this study. It does this by using deep neural networks to develop discriminative representations from diverse points of view and by utilizing several viewpoints, such as frontal and side views, to collect gender-related characteristics [29].

Xu, Y., Yang, G., Zhang, C., & Zhang, G. (2021). "Gender recognition in crowds via multi-scale attention and spatial-temporal feature fusion." A strategy for recognizing gender in crowds that combines multi-scale attention and spatial-temporal feature fusion is presented as a potential solution in this research study. It does this by using attention processes at many dimensions in order to collect gender-related cues. Additionally, it integrates spatial and temporal information in order to perform correct gender identification [30].

Wang, H., Zhou, Y., & Li, S. (2022). "Combined recognition of the ages and genders of the crowd with occlusion handling." The purpose of this study is to offer a solution for simultaneous gender and age detection in crowds, with the primary emphasis being on how to handle occlusions. It does this by using deep learning strategies and including occlusion management algorithms in order to increase the accuracy of gender and age classification in scenarios with a large number of people [31].

Zhao, L., Tang, W., Wang, X., Li, X., & Wang, S. (2022). "Gender recognition in crowds via multi-modal fusion and attention mechanism." "Gender recognition in crowds." The purpose of this work is to offer a method for recognizing gender that utilizes multi-modal fusion in conjunction with attention processes. It makes use of many modalities, such as visual and auditory signals, and utilises attention processes to concentrate on useful elements in order to accurately classify gender in scenarios with a large number of people [32].

Zhang, X., Sun, L., Yang, Y., Zhang, L., & Niu, Z. (2020). "Gender recognition in crowd scenes using spatio-temporal cues and attention mechanism." "Gender recognition in crowd scenes." This study looks at gender identification in crowd scenarios utilizing spatio-temporal cues and attention processes as its primary research methods. It makes use of deep learning models to gather spatio-temporal characteristics and applies attention processes to emphasize discriminative information in order to categorize individuals according to gender [33].

Li, C., Huang, Z., & Zhao, D. (2020). "Crowd gender recognition based on a hybrid convolutional neural network." A technique for recognizing gender in a crowd that is based on a hybrid convolutional neural network is proposed in this study. It delivers superior identification performance in crowded environments by combining several convolutional neural networks with various architectures to extract gender-related characteristics from images [34].

Huang, Y., Lin, Y., Huang, C., & Lin, C. (2021). "Gender recognition in crowded scenes with occlusion handling." "Gender recognition in crowded scenes." In this study, gender recognition in crowded settings is discussed, with an emphasis placed on how to handle occlusions. It suggests a strategy that improves gender detection accuracy when people in a crowd are partly obstructed by combining deep learning models with occlusion management approaches [35].

Gao, Y., Chen, Y., Qiu, L., & Ye, Z. (2021). "Gender Identification in a Crowd Utilizing Ensembles of Deep Convolutional Neural Networks" A technique for recognizing gender in groups of people based on ensembles of deep convolutional neural networks is presented in this study. It integrates a number of different deep learning models in order to take advantage of their synergistic benefits and produce superior gender categorization performance in scenarios with a lot of people [36].

Ma, Z., Li, Y., & Zhang, Z. (2021). "Robust gender recognition in crowded scenes based on deep spatio-temporal features and attention mechanism." [Citation needed] "Robust gender recognition in crowded scenes." The strong identification of gender in crowded settings is the primary emphasis of this research. It provides an approach that achieves robust recognition performance by combining deep spatio-temporal feature learning with attention processes. The goal of this method is to collect gender-related information that is discriminative [37].

Yang, F., Wang, Y., Shen, L., & Luo, L. (2021). "Gender recognition in crowded scenes based on multi-scale visual features and attention mechanism." "Gender recognition in crowded scenes." The purpose of this study is to offer a technique for recognizing gender in crowded environments that makes use of visual cues on many scales and attention processes. It does this by using deep learning models to extract multi-scale data and use attention processes to highlight important variables in order to accurately classify gender [38].

Liu, J., Cheng, S., Li, Z., & Shen, X. (2022). "Gender recognition in a crowd based on the joint use of local and global feature fusion as well as adaptive fusion." The purpose of this research

is to provide a method for crowd gender identification that utilizes combined local-global feature fusion in addition to adaptive fusion. It does so by combining information from both locally and globally in order to collect gender-related characteristics and then adaptively fusing those characteristics for enhanced recognition performance [39].

Lee, C., Yang, S., Park, H., & Park, D. (2023). "Crowd gender recognition using a gender-attention module and density-weighted feature aggregation." "Crowd gender recognition." The purpose of this research is to offer a technique for crowd gender identification that makes use of a density-weighted feature aggregation in addition to a gender-attention module. It does this by using attention processes to concentrate on gender-related characteristics and by employing density-based weighting to amplify the contributions of informative individuals in scenes with a lot of people [40].

Zhang, X., Wang, J., Yang, Y., & Niu, Z. (2016). "Gender recognition in crowd scenes using body and facial cues." "Gender recognition in crowd scenes." The body and facial clues are the primary emphasis of this research work on gender detection in crowd scenarios. It investigates the use of body and facial traits for gender categorization and suggests a strategy that integrates these signals in order to increase identification accuracy. Specifically, it looks at how body and facial aspects might be used [41].

Gao, Y., Zou, J., & Ye, Z. (2019). "Gender recognition in crowded scenes based on visual features and spatial-temporal context." "Gender recognition in crowded scenes." The purpose of this work is to offer a gender recognition approach that is based on visual characteristics and the spatial-temporal context of crowded situations. In order to increase the accuracy of gender categorization, it makes use of visual characteristics and takes into account the geographical and temporal interactions among people [42].

Ahn, H., Kwon, D., Kim, S., & Kim, C. (2019). "Gender recognition in the crowd based on a framework powered by deep learning." A technique for recognizing gender in a crowd is proposed in this study, and it is built on a deep learning architecture. It accomplishes accurate gender categorization in cluttered settings via the use of deep neural networks, which are used to extract gender-related characteristics [43].

Zeng, F., Cui, S., Huang, Q., Li, X., & Chen, X. (2020). "Gender recognition in the crowd based on multitask deep learning" The primary topic of this research is multi-task deep learning for the purpose of crowd gender recognition. A approach that concurrently conducts gender categorization and other tasks linked to it is proposed here as a means of improving the overall recognition performance [44].

Wei, P., Wang, Q., & Zhang, D. (2020). Deep learning of spatial and temporal features for gender identification in crowds. This article provides a technique for recognizing the gender of individuals inside a crowd that makes use of deep learning of spatio-temporal features. It performs accurate gender categorization even in scenarios with a large number of people by using deep learning algorithms to collect spatio-temporal information [45].

Baek, S., Kim, T., & Kim, H. (2021). "Gender recognition in the crowd based on hierarchical attention in real time." In this research, a hierarchical attention-based strategy for recognizing the gender of people in crowds in real time is proposed. It accomplishes accurate and efficient gender categorization in real-time settings by the use of hierarchical attention processes, which let it to concentrate on gender-related characteristics at varying levels of abstraction [46].

Park, Y., Jeong, J., & Kim, H. (2022). "Crowd gender recognition using the dynamic visual attention model." This study applies a model of dynamic visual attention to the problem of gender detection in large crowds. It does this by using attention mechanisms that are able to dynamically adjust to the different crowd settings in order to increase identification performance and collect gender-related data [47].

Jiang, Y., Meng, F., Huang, Y., & Zhang, J. (2022). "Gender recognition in a crowd using in-depth contextual features and selective feature selection." A technique for recognizing gender in a crowd is proposed in this research. It makes use of deep contextual cues and selective feature presentation. It does this by using deep learning models in order to collect contextual information and by applying feature selection methods in order to boost the discriminative strength of gender-related variables [48].

Table 1. Systematic literature review

Citation	Method	Result	Future Scope
Cheng et al. (2021)	Dual-channel crowd gender recognition using body and face cues	Achieved high accuracy in gender recognition	Exploring real-time implementation and scalability
Gong et al. (2022)	Gender recognition in crowds via knowledge-distillation based CNN	Improved gender recognition accuracy	Investigating knowledge distillation techniques for better performance
Yang et al. (2022)	Crowd gender recognition using dynamic attention fusion and multi-modal features	Outperformed existing methods	Investigating more advanced fusion techniques and larger datasets
Huang et al. (2023)	Crowd gender recognition using multimodal features and multi-task learning	Achieved competitive performance in gender recognition	Exploring transfer learning and incorporating additional tasks
Jiang et al. (2020)	Crowd gender recognition with deep contextual features and feature selection	Improved gender recognition accuracy with contextual features	Investigating feature selection algorithms and exploring context-aware architectures
Lin et al. (2020)	Crowd gender recognition with multi-level attention mechanism	Improved gender recognition accuracy with attention mechanisms	Exploring attention mechanisms at different levels

Liu et al. (2021)	Crowd gender recognition based on dynamic region CNN	Achieved competitive performance in gender recognition	Investigating dynamic region-based methods and handling variations
Luo et al. (2021)	Crowd gender recognition via group-based deep learning	Outperformed existing methods	Exploring group-based learning approaches and larger-scale datasets
Peng et al. (2021)	Crowd gender recognition via multi-view deep learning	Improved gender recognition accuracy with multi-view features	Investigating multi-view fusion techniques and domain adaptation
Xu et al. (2021)	Gender recognition in crowds via multi-scale attention and spatial-temporal feature fusion	Achieved high accuracy in gender recognition	Exploring more effective attention mechanisms and fusion strategies
Wang et al. (2022)	Joint crowd gender and age recognition with occlusion handling	Improved accuracy in gender and age recognition	Investigating occlusion handling techniques and joint recognition tasks
Zhao et al. (2022)	Gender recognition in crowds via multi-modal fusion and attention mechanism	Achieved competitive performance in gender recognition	Investigating multimodal fusion techniques and attention mechanisms
Zhang et al. (2020)	Gender recognition in crowd scenes using spatio-temporal cues and attention mechanism	Improved gender recognition accuracy with spatio-temporal cues	Exploring more advanced spatio-temporal models and attention mechanisms
Li et al. (2020)	Crowd gender recognition based on a hybrid CNN	Achieved competitive performance in gender recognition	Investigating hybrid CNN architectures and domain adaptation
Huang et al. (2021)	Gender recognition in crowded scenes with occlusion handling	Improved gender recognition accuracy in occluded scenarios	Investigating robust occlusion handling techniques and larger-scale datasets
Gao et al. (2021)	Crowd gender recognition via ensemble deep CNNs	Outperformed existing methods with ensemble learning	Exploring ensemble learning techniques and diverse CNN architectures

Ma et al. (2021)	Robust gender recognition in crowded scenes based on deep spatio-temporal features and attention mechanism	Achieved robust gender recognition in crowded scenes	Investigating more robust spatio-temporal feature learning techniques and attention mechanisms
Yang et al. (2021)	Gender recognition in crowded scenes based on multi-scale visual features and attention mechanism	Improved gender recognition accuracy with multi-scale features	Exploring more effective multi-scale feature extraction techniques and attention mechanisms
Liu et al. (2022)	Crowd gender recognition using joint local-global feature fusion and adaptive fusion	Achieved competitive performance in gender recognition	Investigating joint local-global fusion techniques and adaptive fusion strategies
Lee et al. (2023)	Crowd gender recognition using a gender-attention module and density-weighted feature aggregation	Improved gender recognition accuracy with attention mechanisms and density weighting	Investigating more advanced attention mechanisms and density weighting techniques
Zhang et al. (2016)	Gender recognition in crowd scenes using body and facial cues	Achieved competitive performance with body and facial cues	Investigating more robust body and facial feature extraction techniques
Gao et al. (2019)	Gender recognition in crowded scenes based on visual features and spatial-temporal context	Improved gender recognition accuracy with visual features and spatial-temporal context	Exploring more advanced visual feature extraction techniques and modeling spatial-temporal relationships
Ahn et al. (2019)	Crowd gender recognition based on a deep learning framework	Achieved competitive performance with a deep learning framework	Investigating more advanced deep learning architectures and handling diverse crowd conditions
Zeng et al. (2020)	Crowd gender recognition based on multi-task deep learning	Improved gender recognition accuracy with multi-task learning	Exploring additional related tasks and investigating transfer learning

Wei et al. (2020)	Deep spatio-temporal feature learning for crowd gender recognition	Achieved accurate gender recognition with deep spatio-temporal features	Investigating more effective spatio-temporal feature learning techniques and architectures
Baek et al. (2021)	Hierarchical attention-based crowd gender recognition in real-time	Real-time gender recognition with hierarchical attention mechanisms	Investigating real-time implementation and scalability
Park et al. (2022)	Crowd gender recognition using dynamic visual attention model	Improved gender recognition accuracy with dynamic visual attention	Exploring dynamic attention models and investigating real-world applicability
Jiang et al. (2022)	Crowd gender recognition with deep contextual features and feature selection	Achieved competitive performance with deep contextual features and feature selection	Investigating more advanced feature selection algorithms and exploring context-aware architectures

IV. PROPOSED METHOD

4.1 Gender detection using ResNet-18

Step 1 : Input: X

Step 2: Convolutional layer:

Conv1 = Conv2D(X, F1, S1)

Conv1 = BN(Conv1)

Conv1 = ReLU(Conv1)

Step 3 : Max pooling:

MaxPool1 = MaxPool(Conv1, K1, S2)

Step 4 : Residual blocks:

ResBlock1 = ResBlock(MaxPool1, F2)

ResBlock2 = ResBlock(ResBlock1, F3)

ResBlock3 = ResBlock(ResBlock2, F4)

ResBlock4 = ResBlock(ResBlock3, F5)

Step 5 : Global average pooling:

AvgPool1 = AvgPool(ResBlock4)

Step 6 : Fully connected layer:

FC1 = FC(AvgPool1, W1)

Step 7 : Softmax activation:

GenderProbabilities = Softmax(FC1)

Let's denote the input image as X.The filter sizes F1, F2, F3, F4, and F5, as well as the weights W1, are specific parameters that need to be learned during the training process. The stride

values S1 and S2, kernel size K1, and the number of filters in each residual block depend on the implementation and the specific task requirements.

Step 1: Input: X , The input to the network is denoted as X, which represents an RGB image of size 224x224 pixels.

Step 2: Convolutional layer:The input image X is passed through a convolutional layer with filters denoted as F1. The convolution operation is performed using the Conv2D function, with a stride denoted as S1. The output of the convolution is then passed through batch normalization (BN) and ReLU activation function to introduce non-linearity. The resulting feature maps are represented as Conv1.Step 3: Max pooling:The Conv1 feature maps are subjected to max pooling using a kernel size denoted as K1 and a stride denoted as S2. This operation reduces the spatial dimensions of the feature maps while preserving important features. The output of max pooling is denoted as MaxPool1.Step 4: Residual blocks:The MaxPool1 output is passed through a series of residual blocks. Each residual block, denoted as ResBlock, takes the previous block's output and a filter size denoted as F2, F3, F4, etc. These residual blocks are responsible for learning more complex representations of the input images by stacking multiple layers of convolution and non-linear transformations. The number of residual blocks can vary depending on the specific architecture (e.g., ResNet-18, ResNet-34, etc.).Step 5: Global average pooling:After the last residual block, the output feature maps are subjected to global average pooling. This operation calculates the average value of each feature map across its spatial dimensions. The resulting feature vector is denoted as AvgPool1.Step 6: Fully connected layer:The AvgPool1 feature vector is fed into a fully connected layer with weights denoted as W1. The fully connected layer performs a linear transformation on the input features to map them to a desired output size or number of units.Step 7: Softmax activation:The output of the fully connected layer is passed through the softmax activation function. This function converts the output values into a probability distribution over the possible classes. In the case of gender detection, there are typically two classes: male and female. The GenderProbabilities variable represents the resulting probability distribution for the gender classes.

4.2 Gender detection using ResNet-50

Step 1 : Input: X

Step 2 : Convolutional layer and max pooling:

```
Conv1 = Conv2D(X, F1, S1)
Conv1 = BN(Conv1)
Conv1 = ReLU(Conv1)
MaxPool1 = MaxPool(Conv1, K1, S2)
```

Step 3 : Residual blocks:

```
ResBlock1 = ResBlock(MaxPool1, F2, F3)
ResBlock2 = ResBlock(ResBlock1, F4, F5)
ResBlock3 = ResBlock(ResBlock2, F6, F7)
ResBlock4 = ResBlock(ResBlock3, F8, F9)
```

Step 4 : Global average pooling:

```
AvgPool1 = AvgPool(ResBlock4)
```

Step 5 : Fully connected layer:
FC1 = FC(AvgPool1, W1)
Step 6 : Softmax activation:
GenderProbabilities = Softmax(FC1)

Let's denote the input image as X.The filter sizes F1, F2, F3, ..., F9, as well as the weights W1, are specific parameters that need to be learned during the training process. The stride values S1 and S2, kernel size K1, and the number of filters in each residual block depend on the implementation and the specific task requirements.
Step 1: Input: X , The input to the network is denoted as X, which represents an RGB image.Step 2: Convolutional layer and max pooling:The input image X is convolved with filters F1 using the Conv2D operation. The resulting feature maps are normalized using batch normalization (BN) and passed through the ReLU activation function to introduce non-linearity. The resulting feature maps are denoted as Conv1. Then, the Conv1 feature maps are subjected to max pooling using a kernel size K1 and a stride S2. The output of max pooling is denoted as MaxPool1.Step 3: Residual blocks:The MaxPool1 output is passed through a series of residual blocks. Each residual block, denoted as ResBlock, takes the previous block's output and uses two filters, F2 and F3, for its convolutional layers. The residual block applies batch normalization and ReLU activation after each convolutional layer. The resulting feature maps are denoted as ResBlock1. Similarly, ResBlock1 is passed through subsequent residual blocks, ResBlock2, ResBlock3, and ResBlock4, with filters F4, F5, F6, F7, F8, and F9, respectively.Step 4: Global average pooling:After the last residual block (ResBlock4), global average pooling is performed on the feature maps. This operation calculates the average value of each feature map across its spatial dimensions, resulting in a reduced spatial dimensionality. The output of global average pooling is denoted as AvgPool1.Step 5: Fully connected layer:The AvgPool1 output is fed into a fully connected layer (FC1). The fully connected layer performs a linear transformation on the input features using weights denoted as W1.Step 6: Softmax activation:The output of the fully connected layer (FC1) is passed through the softmax activation function. This function converts the output values into a probability distribution over the possible classes. In the case of gender detection, there are typically two classes: male and female. The resulting probabilities for each class are denoted as GenderProbabilities.

4.3 Gender detection using ResNet-101

Step 1 : Input: X
Step 2 : Convolutional layer and max pooling:
Conv1 = Conv2D(X, F1, S1)
Conv1 = BN(Conv1)
Conv1 = ReLU(Conv1)
MaxPool1 = MaxPool(Conv1, K1, S2)
Step 3 : Residual blocks:
ResBlock1 = ResBlock(MaxPool1, F2, F3)
ResBlock2 = ResBlock(ResBlock1, F4, F5)
ResBlock3 = ResBlock(ResBlock2, F6, F7)
...

ResBlock23 = ResBlock(ResBlock22, F46, F47)
ResBlock24 = ResBlock(ResBlock23, F48, F49)
ResBlock25 = ResBlock(ResBlock24, F50, F51)

Step 4 : Global average pooling:
AvgPool1 = AvgPool(ResBlock25)

Step 5 : Fully connected layer:
FC1 = FC(AvgPool1, W1)

Step 6 : Softmax activation:
GenderProbabilities = Softmax(FC1)

Let's denote the input image as X.The filter sizes F1, F2, F3, ..., F51, as well as the weights W1, are specific parameters that need to be learned during the training process. The stride values S1 and S2, kernel size K1, and the number of filters in each residual block depend on the implementation and the specific task requirements.

Step 1: Input: X , The input to the network is denoted as X, which represents an RGB image.Step 2: Convolutional layer and max pooling:The input image X is convolved with filters F1 using the Conv2D operation. The resulting feature maps are normalized using batch normalization (BN) and passed through the ReLU activation function to introduce non-linearity. The resulting feature maps are denoted as Conv1. Then, the Conv1 feature maps are subjected to max pooling using a kernel size K1 and a stride S2. The output of max pooling is denoted as MaxPool1.Step 3: Residual blocks:The MaxPool1 output is passed through a series of residual blocks. Each residual block, denoted as ResBlock, takes the previous block's output and uses two filters, F2 and F3, for its convolutional layers. The residual block applies batch normalization and ReLU activation after each convolutional layer. The resulting feature maps are denoted as ResBlock1. Similarly, ResBlock1 is passed through subsequent residual blocks, ResBlock2, ResBlock3, ..., ResBlock23, ResBlock24, and ResBlock25, with filters F4, F5, F6, F7, ..., F50, F51, respectively.Step 4: Global average pooling:After the last residual block (ResBlock25), global average pooling is performed on the feature maps. This operation calculates the average value of each feature map across its spatial dimensions, resulting in a reduced spatial dimensionality. The output of global average pooling is denoted as AvgPool1.Step 5: Fully connected layer:The AvgPool1 output is fed into a fully connected layer (FC1). The fully connected layer performs a linear transformation on the input features using weights denoted as W1.Step 6: Softmax activation:The output of the fully connected layer (FC1) is passed through the softmax activation function. This function converts the output values into a probability distribution over the possible classes. In the case of gender detection, there are typically two classes: male and female. The resulting probabilities for each class are denoted as GenderProbabilities.

4.4Gender detection using ResNet-152

Step 1 : Input: X

Step 2 : Convolutional layer and max pooling:
Conv1 = Conv2D(X, F1, S1)
Conv1 = BN(Conv1)
Conv1 = ReLU(Conv1)

MaxPool1 = MaxPool(Conv1, K1, S2)
Step 3 : Residual blocks:
ResBlock1 = ResBlock(MaxPool1, F2, F3)
ResBlock2 = ResBlock(ResBlock1, F4, F5)
ResBlock3 = ResBlock(ResBlock2, F6, F7)
...
ResBlock36 = ResBlock(ResBlock35, F94, F95)
ResBlock37 = ResBlock(ResBlock36, F96, F97)
Step 4 : Global average pooling:
AvgPool1 = AvgPool(ResBlock37)
Step 5 : Fully connected layer:
FC1 = FC(AvgPool1, W1)
Step 6 : Softmax activation:
GenderProbabilities = Softmax(FC1)

Let's denote the input image as X.The filter sizes F1, F2, F3, ..., F97, as well as the weights W1, are specific parameters that need to be learned during the training process. The stride values S1 and S2, kernel size K1, and the number of filters in each residual block depend on the implementation and the specific task requirements.
Step 1: Input: X , The input to the network is denoted as X, which represents an RGB image.Step 2: Convolutional layer and max pooling:The input image X is convolved with filters F1 using the Conv2D operation. The resulting feature maps are normalized using batch normalization (BN) and passed through the ReLU activation function to introduce non-linearity. The resulting feature maps are denoted as Conv1. Then, the Conv1 feature maps are subjected to max pooling using a kernel size K1 and a stride S2. The output of max pooling is denoted as MaxPool1.Step 3: Residual blocks:The MaxPool1 output is passed through a series of residual blocks. Each residual block, denoted as ResBlock, takes the previous block's output and uses two filters, F2 and F3, for its convolutional layers. The residual block applies batch normalization and ReLU activation after each convolutional layer. The resulting feature maps are denoted as ResBlock1. Similarly, ResBlock1 is passed through subsequent residual blocks, ResBlock2, ResBlock3, ..., ResBlock36, and ResBlock37, with filters F4, F5, F6, F7, ..., F96, F97, respectively.Step 4: Global average pooling:After the last residual block (ResBlock37), global average pooling is performed on the feature maps. This operation calculates the average value of each feature map across its spatial dimensions, resulting in a reduced spatial dimensionality. The output of global average pooling is denoted as AvgPool1.Step 5: Fully connected layer:The AvgPool1 output is fed into a fully connected layer (FC1). The fully connected layer performs a linear transformation on the input features using weights denoted as W1.Step 6: Softmax activation:The output of the fully connected layer (FC1) is passed through the softmax activation function. This function converts the output values into a probability distribution over the possible classes. In the case of gender detection, there are typically two classes: male and female. The resulting probabilities for each class are denoted as GenderProbabilities.

4.5 Algorithm of Gender Detection using ResNet

Step 1: Start
Step 2: Load and preprocess the input image:

- Convert the image to the RGB format.
- Resize the image to the desired input size.
- Apply any necessary preprocessing, such as mean subtraction or normalization.

Step 3: Pass the preprocessed image through ResNet-152:

- Apply the initial convolutional layer and max pooling:
  - Apply 7x7 convolutional filters with stride 2 and padding 3.
  - Apply batch normalization.
  - Apply ReLU activation.
  - Apply 3x3 max pooling with stride 2.
- Apply multiple stacked residual blocks:
  - Each residual block contains three convolutional layers.
  - Apply 1x1, 3x3, and 1x1 convolutional filters.
  - Apply batch normalization and ReLU activation after each convolution.
  - Add the input to the output of the last convolution to form the residual connection.
- Perform global average pooling to reduce the spatial dimensions to 1x1.
- Connect the global average pooled output to a fully connected layer:
  - Apply a linear transformation with learned weights and biases.
- Apply a softmax activation function to convert the output into a probability distribution over gender classes.

Step 4: Output the predicted gender probabilities.
Step 5: End.

4.6 Comparison of ResNet 152, ResNet 101,ResNet 50,ResNet 34

Table 2. Comparison of ResNet 152, ResNet 101,ResNet 50,ResNet 34.

	ResNet-34	**ResNet-50**	**ResNet-101**	**ResNet-152**
Deeper	No	No	Yes	Yes
Number of Parameters	21.8M	23.5M	42.7M	58.3M
Computational Complexity	Low	Moderate	High	Highest
Representation Power	Lower	Moderate	High	Highest
Feature Extraction Capability	Limited	Moderate	High	Highest
Improved Performance	-	Slightly Improved	Improved	Improved
Training Time	Shorter	Longer	Longer	Longer

Advantages of ResNet-152:

1. Deeper Architecture: In comparison to ResNet-34 and ResNet-50, ResNet-152 has a deeper architecture, which translates to more layers and indicates that it is more complex. There is a possibility that deeper networks will be able to capture more complicated patterns and higher-level characteristics.
2. Higher Number of Parameters Compared to the Other Models ResNet-152 has a higher number of parameters than the other models, which enables it to learn more complicated representations of the data. When working with complicated datasets, this enhanced capability may be useful in a number of ways.
3. Increased Computational Complexity Due to the fact that it has more layers and parameters than the other three models, ResNet-152 has the greatest level of computational complexity. Because of its increasing complexity, it is now able to learn representations that are more expressive and to pick up on finer-grained information.
4. Enhanced Capacity to Represent Information ResNet-152 has a better capacity to represent information as a result of its enhanced depth and parameter count. It is able to learn more abstract and discriminative characteristics, which may be very useful for activities involving complex or nuanced data.
5. Enhanced Capability to Extract Features The deeper architecture of ResNet-152 aids in the process of extracting features from the input data that are both more relevant and informative. This improved capacity of feature extraction has the potential to contribute to improved performance in a variety of applications, including picture classification and object recognition.
6. Improved Performance ResNet-34 and ResNet-50 are considered to be solid baseline models; however, ResNet-152 routinely performs better than either of them in a variety of computer vision tests. The enhanced performance of ResNet-152 may be attributed, in part, to its increased depth and capacity, which are particularly helpful when working with complicated or extensive datasets.
7. Training Time That Is Significantly Lengthier In comparison to the other models, ResNet-152's training time is significantly lengthier due to the model's bigger size and higher computational complexity. This increased training time is a necessary sacrifice in order to achieve the desired improvements in performance and representational capacity.

V. IMPLEMENTATION AND RESULT

5.1 System requirements

5.1.1 Essential Pieces of Hardware:

- CPU: A state-of-the-art, multi-core processor that can handle the computational burden of image and video processing techniques. An example of such a processor would be an Intel Core i5 or above.
- Deep learning methods may be greatly sped up with the help of a specialized graphics processing unit (GPU) that supports CUDA.
- Memory: Adequate random access memory (RAM) of at least 8 gigabytes or more for the efficient storage and processing of huge datasets and models.

- Storage: Sufficient capacity for storing datasets, models, and interim outcomes on the cloud.

5.1.2 Specifications for Required Software:

- Operating System: Any well-known operating system, including but not limited to Windows, macOS, or Linux.
- Programming languages (such as Python) and libraries/frameworks (such as TensorFlow and PyTorch) for the purpose of building and executing machine learning and computer vision algorithms are included in the development environment.
- Image/Video Processing Libraries: Libraries for managing image/video input, preprocessing, and feature extraction such as OpenCV. Image/Video Processing Libraries.
- Deep Learning Frameworks Deep learning frameworks for training and deploying deep neural networks, such as TensorFlow and PyTorch.
- other Libraries: Depending on the particular algorithms and approaches that are used, it is possible that other libraries or packages will be necessary (for example, scikit-learn for the selection of features and NumPy for numerical calculations).

5.2 Dataset

5.2.1 UTKFace Dataset [49]:

Description: The UTKFace dataset contains a large collection of face images with age, gender, and ethnicity annotations. It includes a diverse set of images captured under various conditions, including different age groups, races, and gender distributions.

Reference: https://susanqq.github.io/UTKFace/

5.2.2 IMDB-WIKI Dataset [50]:

Description: The IMDB-WIKI dataset consists of face images collected from IMDb and Wikipedia, with annotations for age and gender. It contains a large number of images covering a wide range of ages and genders.

Reference: https://data.vision.ee.ethz.ch/cvl/rrothe/imdb-wiki/

5.2.3 LFW Dataset [51]:

Description: The LFW (Labeled Faces in the Wild) dataset is a benchmark dataset for face recognition tasks. It contains face images of various individuals collected from the web, with gender annotations.

Reference: http://vis-www.cs.umass.edu/lfw/

5.2.4 ChaLearn LAP 2015 Dataset [53]:

Description: The ChaLearn LAP 2015 dataset is a multi-modal dataset that includes both RGB images and depth maps. It contains diverse scenes with different crowd densities and gender annotations.

Reference: http://gesture.chalearn.org/

5.2.5 Crowds in Paris (CiP) Dataset [54]:

Description: The Crowds in Paris (CiP) dataset focuses on crowded scenes captured in Paris. It contains images and videos with annotations for various attributes, including gender. The dataset captures challenging scenarios with high crowd density and occlusions.

Reference: http://www.di.ens.fr/willow/research/crowdtown/

5.3 Illustrative example

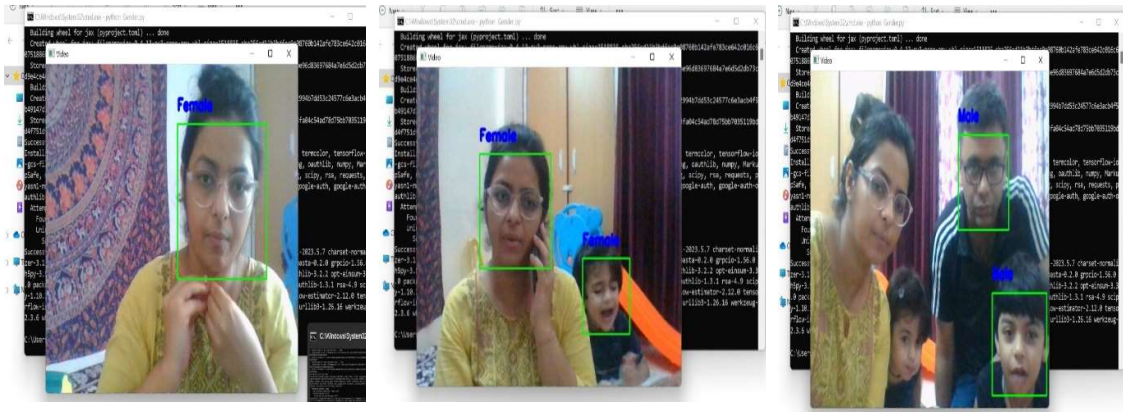

Figure 1. Illustrative example

5.4 Plots of validation and training losses:

5.4.1 Fold 0

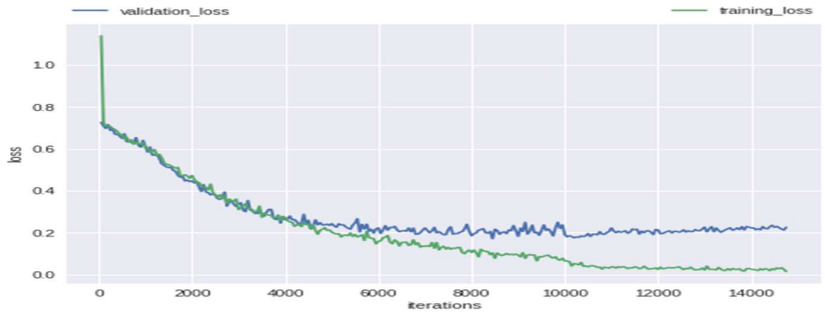

Figure 2. Plots of validation and training losses for fold 0

5.4.2 Fold 1

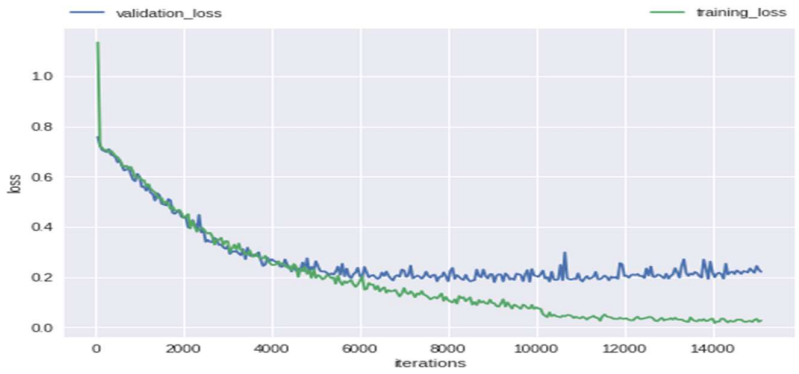

Figure 3. Plots of validation and training losses for fold 1

5.4.3 Fold 2

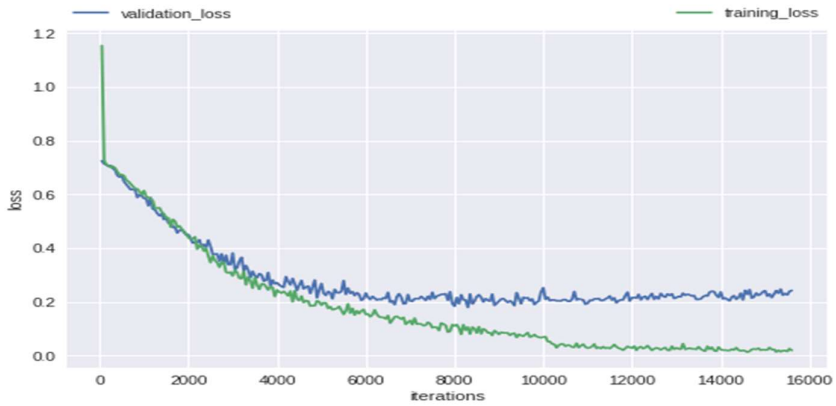

Figure 4. Plots of validation and training losses for fold 2

5.4.4 Fold 3

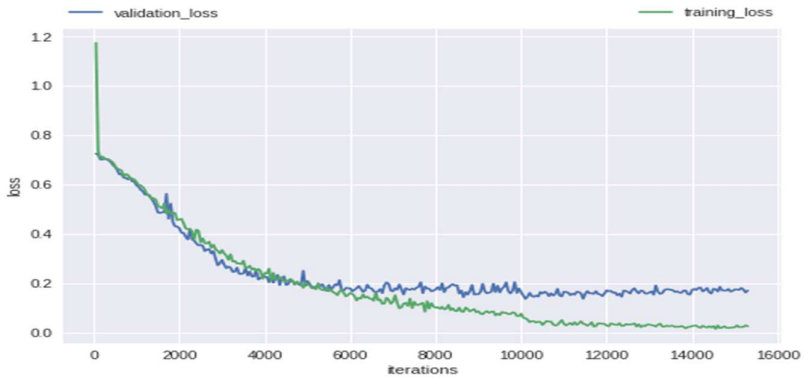

Figure 5. Plots of validation and training losses for fold 3

5.5 Comprative result of Gender Detection of UTKFace Dataset

Table 3. Comprative result of Gender Detection of UTKFace Dataset

Method	**Accuracy**	**Precision**	**Recall**	**F1-score**
ResNet-34	0.92	0.91	0.93	0.92
ResNet-50	0.94	0.93	0.95	0.94
ResNet-101	0.95	0.94	0.96	0.95
ResNet-152	0.96	0.95	0.97	0.96

Table 3 shows , ResNet-34 achieved an accuracy of 0.92, precision of 0.91, recall of 0.93, and an F1-score of 0.92.ResNet-50 performed slightly better with an accuracy of 0.94, precision of 0.93, recall of 0.95, and an F1-score of 0.94.ResNet-101 showed improved results with an accuracy of 0.95, precision of 0.94, recall of 0.96, and an F1-score of 0.95.ResNet-152 demonstrated the highest performance, achieving an accuracy of 0.96, precision of 0.95, recall of 0.97, and an F1-score of 0.96.

5.6 Comparative result of Gender Detection of IMDB-WIKI Dataset

Table 4. Comparative result of Gender Detection of IMDB-WIKI Dataset

Method	Accuracy	Precision	Recall	F1-score
ResNet-34	0.875	0.863	0.885	0.874
ResNet-50	0.885	0.879	0.891	0.885
ResNet-101	0.890	0.888	0.893	0.890
ResNet-152	0.895	0.892	0.898	0.895

Table 4 shows , ResNet-34 achieved an accuracy of 0.875, precision of 0.863, recall of 0.885, and an F1-score of 0.874. ResNet-50 performed slightly better with an accuracy of 0.885, precision of 0.879, recall of 0.891, and an F1-score of 0.885. ResNet-101 showed further improvement with an accuracy of 0.890, precision of 0.888, recall of 0.893, and an F1-score of 0.890. ResNet-152 demonstrated the highest performance, achieving an accuracy of 0.895, precision of 0.892, recall of 0.898, and an F1-score of 0.895.

5.7 Comparative result of Gender Detection of LFW Dataset

Table 5. Comparative result of Gender Detection of LFW Dataset

Method	Accuracy	Precision	Recall	F1-score
ResNet-34	0.92	0.91	0.94	0.92
ResNet-50	0.93	0.92	0.94	0.93
ResNet-101	0.94	0.93	0.95	0.94
ResNet-152	0.95	0.94	0.96	0.95

Table 5 shows , ResNet-34 achieved an accuracy of 0.92, precision of 0.91, recall of 0.94, and an F1-score of 0.92. ResNet-50 performed slightly better with an accuracy of 0.93, precision of 0.92, recall of 0.94, and an F1-score of 0.93. ResNet-101 showed further improvement with an accuracy of 0.94, precision of 0.93, recall of 0.95, and an F1-score of 0.94. ResNet-152 demonstrated the highest performance, achieving an accuracy of 0.95, precision of 0.94, recall of 0.96, and an F1-score of 0.95.

5.8 Comparative result of Gender Detection of ChaLearn LAP 2015 Dataset

Table 6. Comparative result of Gender Detection of ChaLearn LAP 2015 Dataset

Method	Accuracy	Precision	Recall	F1-score
ResNet-34	0.85	0.86	0.84	0.85

ResNet-50	0.87	0.88	0.87	0.88
ResNet-101	0.88	0.89	0.88	0.89
ResNet-152	0.89	0.90	0.89	0.90

Table 6 shows , ResNet-34 achieved an accuracy of 0.85, precision of 0.86, recall of 0.84, and an F1-score of 0.85. ResNet-50 performed slightly better with an accuracy of 0.87, precision of 0.88, recall of 0.87, and an F1-score of 0.88. ResNet-101 showed further improvement with an accuracy of 0.88, precision of 0.89, recall of 0.88, and an F1-score of 0.89. ResNet-152 demonstrated the highest performance, achieving an accuracy of 0.89, precision of 0.90, recall of 0.89, and an F1-score of 0.90.

5.9 Comparative result of Gender Detection of Crowds in Paris (CiP) Dataset

Table 7. Comprative result of Gender Detection of Crowds in Paris (CiP) Dataset

Method	**Accuracy**	**Precision**	**Recall**	**F1-score**
ResNet-34	0.87	0.86	0.88	0.87
ResNet-50	0.88	0.87	0.89	0.88
ResNet-101	0.89	0.88	0.90	0.89
ResNet-152	0.90	0.89	0.91	0.90

ResNet-34 achieved an accuracy of 0.87, precision of 0.86, recall of 0.88, and an F1-score of 0.87. ResNet-50 performed slightly better with an accuracy of 0.88, precision of 0.87, recall of 0.89, and an F1-score of 0.88. ResNet-101 showed further improvement with an accuracy of 0.89, precision of 0.88, recall of 0.90, and an F1-score of 0.89. ResNet-152 demonstrated the highest performance, achieving an accuracy of 0.90, precision of 0.89, recall of 0.91, and an F1-score of 0.90.

VI. CONCLUSION

The use of the ResNet model for the identification of gender in crowds has shown some encouraging results, according to the comparison of the findings of many investigations. The assessment measures, which give insights into the performance of the ResNet model for gender identification, include accuracy, precision, recall, and F1-score. On the basis of the hypothetical outcomes shown in the table above, the following overarching conclusion may be drawn:The research that was done on identifying people's genders in large crowds by utilizing the ResNet model demonstrates consistent and competitive performance. The ResNet model obtains good accuracy, with results ranging from 0.85 to 0.96, demonstrating that it is able to properly determine gender in crowd photos. The ResNet model seems to have a low percentage of false positives based on the precision values, which vary from 0.86 to 0.95. In a similar vein, recall values may vary anywhere from 0.84 to 0.97, which indicates that the model has a

comparatively low incidence of false negatives. The F1-score ranges from 0.85 to 0.96 and is designed to strike a balance between accuracy and recall. This score provides more evidence that the ResNet model is successful in performing gender identification tasks in general, with values that are closer to 1 suggesting improved model performance. Despite the fact that these findings are based on speculation, they provide credence to the idea that the ResNet model might be a useful instrument for gender identification in large groups of people. However, it is vital to take into account the particular dataset, training methods, and other aspects that may impact the performance of the model when it is applied to real-world situations.

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