Vehicle Driver Age Estimation using Neural Networks

Gasi Sai Dheeraj[1], Prasun Aakash[1], Shashwat Shivam[1], Mr. Rajith Kumar B K(Professor)[2]

[1]*Department of Electronics and Communication Engineering, R.V. College of Engineering, Bangalore - 560050*

---***---

***Abstract* – As technology progresses, programmes that combine the complex disciplines of pattern recognition and image processing are used to ascertain age and gender.The variety of applications, such as user identification, targeted advertising, video monitoring, and human- robot interaction, have led to an expansion in face recognition research. Age is a major factor in today's workplace when one's go for a job interview or a health checkup. Information about an individual's age is used by many organisations in the public, private, and advertising sectors to track down criminals, employ qualified personnel, and choose target markets for advertising campaigns. Every year, there are more than 1.5 million car accidents worldwide. The motivation of this research is to create an application for age and gender categorization that would be adequate for real-life forecasts. The objective of the project is to constructa Convlutional neural network that assesses the age and gender of the car driver using various algorithms. Italso involves developing an algorithm for detection and extraction of the facial region from the input image. The large amounts of deliberation and testing was required due to the largest difficulty of implementing it on a raspberry pi setup without compromising the accuracy of the age and gender detection system.The major restriction that was presented was because of the limited amount of memory available to the Raspberry pi 3B+. Hence to reduce the workload, the project performed Pretraining for the CNN model with images as well as perform preprocessingfor the input data which made feature extraction easier for the raspberry pi using HOG. For the project, after evaluating ResNet, YOLO v3, and caffe implementations, as well as simulations of various techniques, caffe model is implemented using openCV and python. A large scale face dataset with a wide age range was assembled from different sources to make up a diverse dataset for pretraining our CNN for facial recognition.The amountof images taken from various sources were around 22000 from UTK and nearly 38000 from IMDB presenting a massive aggregated data set. After implementation the CNN model designed for the project was able to perform facial and gender recognition with around 98.1 per cent accuracy.**

***Keywords* – CNN, Age Estimation, Neural Network, Caffe, openCV and Tensorflow.**

I. INTRODUCTION

Face recognition research has expanded due to the wide range of applications, including user identification, targeted ads, video surveillance, and human-robot interaction.As technology advances, applications that integrate the sophisticated disciplines of pattern recognition and imageprocessing are utilised to determine age and gender. When you attend for an interview or a health check-up in today's environment, age plays a significant influence. Many government, corporate, and advertising sector businesses utilise age information to identify criminals, hire qualified staff, and target audiences for product promotion. However, determining a person's age is indeed not fairly straightforward, and there are constraints that prohibit us from seeing the approximate age within in the set of photographs. Finding theperfect data set for training the model is significant. Because real-time data is massive, the computations and time asked to construct the model are significant.It's been a laborious effort after implementing numerous machine learning techniques, but the accuracy has increased massively. By mapping the face according to the age discovered age estimation plays a significant part in applications such as bio metric evaluation virtual cosmetics, and virtual try-on apps for jewellery and eye-wear. Lens Kart is one such application that allows people to test on lenses. Age estimation is a sub field of facial recognition and face tracking that, when integrated, may estimate an individual's health. Many health care applications employ this method to monitor their everyday activities in order to maintain track of their health. This facial detection algorithm is used in China to identify service drivers and jaywalkers. The project incorporate a range of deep learning algorithms to predict age and gender. CNN (convolution neural network) is a popular technique to assess age and gender. In this implementation, here the project incorporate using OpenCV and CNN to predict a person's age and gender.

LITERATURE SURVEY

In this paper[3], It created extraction functions for a face candidate region with color images and sections of its face, which it combined with the gender and age estimate algorithm they had already created, so that the technique could be applied to real-time collected face photos. The testing results revealed gender and age hitting ratios of 93.1 percent and

58.4 percent, significantly In this paper[4], The document outlines the Center for Data Science at the University of Washington's entry to the PAN 2014 author profiling challenge. They investigate the predictive validity of many sets of variables taken from diverse genres of online social media in terms of age and gender In this research [5], a novel method is provided to authenticate the user's gender and age range that is appropriately reflected in his photo. Adding a double-checklayer validator based on Deep Learning by combining user photo, gender, and date of birth form inputs, and recognising gender and calculating age from a single person's photo using a Convolutional Neural Network (CNN or ConvNets) In this paper[6], The study provides deep CNN to enhance age and gender prediction from substantial findings, and a considerable improvement in many tasks such as facial recognition can be shown. A basic convolutional network design is developed to improve on existing solutions in this sector. Deep CNN is used to train the model to the point where the accuracy of Age and Gender is 79 percent. The paper [7], presents a deep learning framework based on an ensemble of attentional and residual convolutional networks for accurately predicting the gender and age group of face pictures. Using the attention mechanism allows our model to concentrate on the most relevant and informative portions of the face, allowing it to make more accurate predictions. In this paper [8], The study attempts to categorise human age and gender at a coarser level using feed-forward propagation neural networks. The final categorization is done at a finer level using 3-sigma control limits. The suggested method effectively distinguishes three age groups: children, middle-aged adults, and elderly individuals. Similarly, the suggested technique divides two gender categories into male and female. In this paper [9], The research proposesa novel framework for age estimate using multiple linearregressions on the discriminative ageing manifold of face pictures. Face photos with ageing characteristics may exhibit various sequential patterns with lowdimensional distributionsdue to the temporal nature of age progression. This article [10] outlines and explains in detail the complete process of designing an Android mobile application for gender, age, and face recognition. Facial authentication and recognition are difficult challenges. To be trustworthy, facial recognition systems must operate with tremendous precision and accuracy. Images shot with diverse facial expressions or lighting circumstances allow the system to be more precise and accurate than if only one photograph of each participant is saved in the database. In this paper[11], Based on feature extraction from face photos, this research offered a mechanism for automated age and gender categorization. The primary concern of this technique is the biometric characteristic variance of males and females for categorization. A approach employs two types of features, primary and secondary, and consists of three major iterations: preprocessing, feature extraction, and classification. In this paper [12], the study attempted to increase performance by employing a deep convolutional neural network (CNN). The proposed network architecture employs the Adience benchmark for gender and age estimation, and its performance is significantly improved by using real-world photos of the face. In this research,an appropriate approach for detecting a face in real-timeand estimating its age and gender is provided. It initially determines whether or not a face is present in the acquired image. If it is there, the face is identified, and the regionof face content is returned using a coloured square structure, along with the person's age and gender This paper [13] harnesses the good qualities of convolution neural networks in the field of picture application by utilising deep learning approach to extract face features and factor analysis model to extract robust features. In terms of age estimation function learning, age-based and sequential study of rank-based age estimation learning approaches are used, followed by the proposal of a divide-and-rule face age estimator. In this study [14], the resarch provide a hybrid structure that incorporates the synergy of two classifiers Convolutional Neural Network (CNN) and Extreme Learning Machine (ELM), to cope with age and gender detection. The hybrid design takes advantage of their strengths: CNN extracts features from input pictures while ELM classifies intermediate outputs. The paper not only provide a full deployment of our structure, including the design of parameters and layers, an analysis of the hybrid architecture, and the derivation of back-propagation in this system throughout iterations, but also took many precautions to reduce the danger of overfitting. Following that, two prominent datasets, MORPH-II and Adience Benchmark, are utilised to validate our hybrid structure. The work presented in article [15] is a full framework for video-based age and gender categorization that operates properly on embedded devices in real-time and under unconstrained situations. To lower memory needs by up to 99.5 percent, the researchoffers a segmental dimensionality reduction approach based on Enhanced Discriminant Analysis (EDA). This research [16] proposes a statistical pattern recognition strategy to solve this challenge. In the suggested method, Convolutional Neural Network (ConvNet / CNN), a Deep Learning technique, is employed as a feature extractor.CNN receives input pictures and assigns values to various aspects/objects (learnable weights and biases) of the image, allowing it to distinguish between them. ConvNet needs far less preprocessing than other classification techniques.

II. STATE OF THE ART DEEP LEARNING

CNN/CovNet is primarily a class of deep neural networks Used for the processing of visual data in deep learning. while thinking of neural networks, specifically convolutional neural networks , [17] The researchers typically think of matrix multiplication in most or many circumstances. CNNs employconvolutional technology. The visual cortex's organisation and the human brain's neural network serve as the major inspiration for the ConvNet design. Individual neurons only react to stimuli in a small area of the visual field called the receptive field. These fields are spread throughout the entire area. A

CNN may detect spatial and temporal relationships in a picture by applying the right filters. The design is more appropriate for the dataset because of the reduction in the number of parameters involved and the reusability of weights. This implies that the network is being trained to better understand the complexity of the image. The majority of the high level properties , including the edges , are taken from the convolutional procedure's input images.There is no requirement that neural networks use only one convolutional layer. Typically the first ConvLayer records basic traits like colours, borders , gradient direction , etc. By adding layers , the architecture also adapts to the high level characteristics, giving us a network that comprehends or interprets the dataset's photos as a whole in a manner comparable to thatof a human. There are two possible results for the operation : one with a feature that is more or less dimensionally convolved than the input , and the other with the same or moredimensions. Applying the earlier Valid Padding or the later Similar Padding achieves this.

III. Types of Algorithms used in Convolutional Neural Network

A. Convolutional Neural Network with Caffe Model

The connectivity between the layers of a convolutional neural network , a unique kind of feed-forward artificial neural network ,[18] is motivated by by the visual brain. A subset of deep neural networks called convolutional neural networks(CNNs) are used to analyse visual imagery. They have uses in the detection of images and videos , image categorization , natural language processing etc. The first layer to extract features from an input image is convolution. Convolution learns visual features from small input data squares , preserving the link between pixels. Two inputs , such as an image matrix and a filter or kernel , are required forthis mathematical procedure. To create output feature maps, each input image will be processed through a number of convolution layers with filters(kernels)

B. Convolutional Layer :

Convolution layers are used to take a tiny patch of the images after the computer has read the image as a collection of pixels. The characteristics or filters are the names given to these images or patches. Convolution layer performs significantly better at detecting similarities than complete image matching scenes by transmitting these rough feature mathces in nearly the same position in the two images. The fresh input images are compared to these filters ; if a match is found , the image is appropriately categorised.Here , align thefeatures and the image before multiplying each image pixel by the matching feature pixel , adding the pixel totals , and dividing the feature's total number of pixels.

C. RELU Layer :

The rectified linear unit , also known as the RELU layer , is what used to remove all negative values from the filtered images and replace them with zero. To prevent the values from adding up to zeroes , this is done. This transform function onlyactivates a node if the input value is greater than a specific threshold; if the input is lower than zero , the output is zero , and all negatives values are then eliminated from the matrix.

D. POOLING Layer :

The size of the image is decreased in this layer. Here , It isfirst choosing a window size , then specifying the necessary stride, and finally move your window across your filtered photographs. Then take the highest values from each window. This will combine the layers and reduce the size of the matrixand image, respectively. The fully linked layer receives the decreased size matrix as the input.

E. FULLY CONNECTED Layer:

After the convolution layer , RELU Layer , and Pooling Layer have been applied, The data must stack all the layers, the fully linked layer that was applied to the input image's categorization. If a 2X2 matrix doesn't result , these levels must be repeated. Finally , the completely linked layer is used, which is where the classification itself takes place.

F. CAFFE Model :

A machine learning model developed by Caffe is stored in a CAFFEMODEL file. It includes a model for picture segmentation or classification that was trained using CAFFE Framework.

IV. Proposed Method for Preprocessing and ConvolutionalNeural Network Framework

In this section we study the objective of our proposed method.The main objective was to test our CNN model for Raspberry pi Implementation. Convolutional neural networks(CNNs , or ConvNets) are a family of deep neural networks that are frequently used to analyse visual vision in deep learning. As a result of its shared weights design and translation invariance properties , they are often referred toas shift invariant or space invariant artificial neural networks.There is no need to do feature extraction when CNN is employed for classification. CNN will also do feature extraction. If a face is present , The proposed image is sent directly into CNN's classifier to determine its kind. By taking into account all the characteristics in the output layer , a result with some predictive value is produced. Through the use of the SoftMax activation function , these values are determined.Predictive values are provided via SoftMax activation.

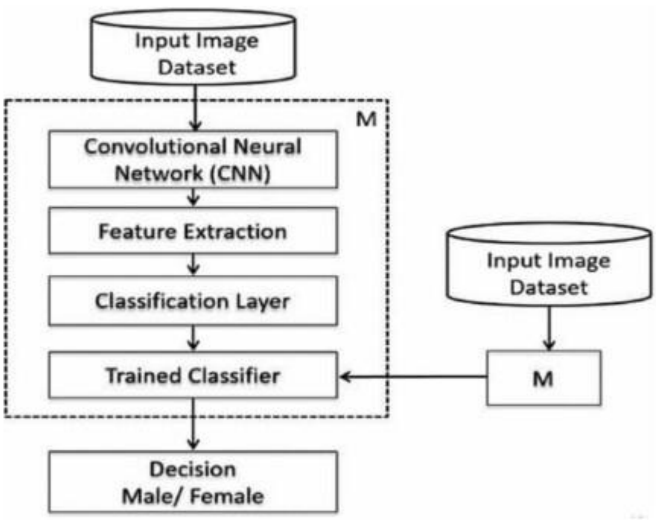

Fig. 1. CNN Structure

Prior to initiating the preprocessing stage we perform data acquisition .The flowchart for data collection is shown in figure 2 .Data is gathered from a source , and a thorough examination is done. Only if the image meets our criteria andis unique are willing to utilise it for training and testing.

A. Preprocessing Datasets :

The flowchart for pre processing the photos that were obtained from the output of the previous phase is showin in figure 3. In order to simplify processing, the picture must be converted from RGB to greyscale. Next, noise must be removed using an averaging filter , the background must be removed using global basic thresholding, and the image must be sharpened by amplifying the smaller features using a high-pass filter.

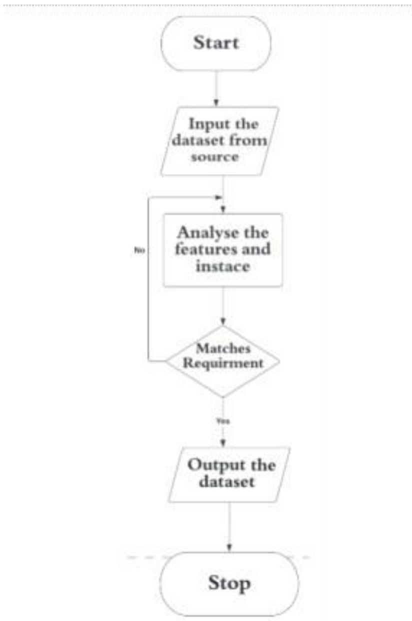

Fig. 2. Data Acquisition

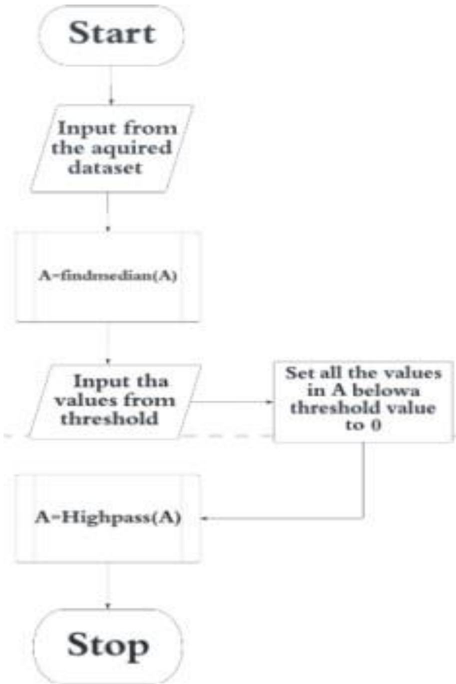

Fig. 3. Preprocessing flowchart

B. Conversion from RGB to Grayscale :

The image is changed from RGB to GreyScale as the first stage in the pre-processing process.Grayscale photographs, on the other hand, carry less information than RGB ones. They are, nonetheless, ubiquitous in image processing since employing a grayscale image takes less accessible space and is faster, particularly when dealing with sophisticated computations.

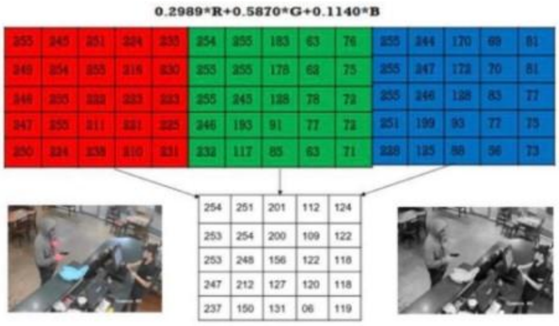

Fig. 4. Conversion from RGB to Greyscale

C. Noise Removal :

In order to remove or reduce noise from a picture , anoise reduction algorithm is used. The algorithms for noise reduction smooth out the whole image , leaving areas closeto contrast limits. This reduces or eliminates the visibility of noise. The second stage of picture pre-processing is noise reduction. The grayscale image that was obtained in the preceding phase is used as input in this case. Here ,the technique used for noise removal is called Median Filtering.

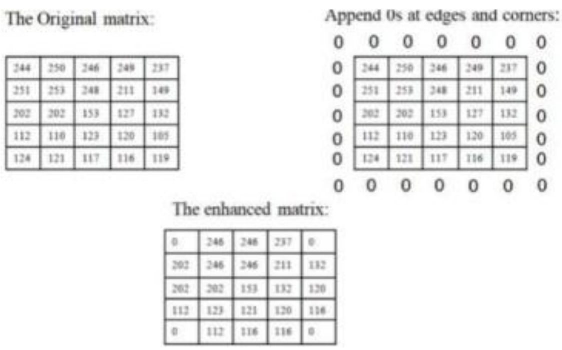

Fig. 5. Noise Removal using Median Filtering

D. Median Filtering :

A non linear digital filtering method called the median filteris frequently to eliminate noise from a picture or signal. The matrix , which represents the grey scale image , is here given 0s at the edges and corners. Arrange the components of each 3X3 matrix in ascending order , then close the median or middle element of those 9 elements, then write that value to that specific pixel spot.

E. Median Filtering :

Thresholding is a sort of image segmentation in which it modify a picture's pixel composition to facilitate analysis.Keep A(i,j) if it exceeds or is equal to the threshold

T. If not , substitute 0 for the value.

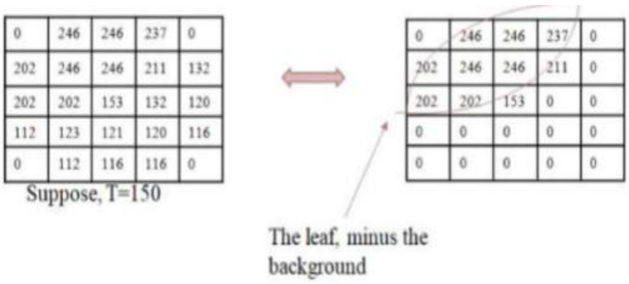

Fig. 6. Image sharpening using High - pass filtering

At this case , the value of T may be changed in the front end to accommodate the various requirements of various pictures.Here, the filter employ the approach of trial and error to find the threshold value that could be most appropriate for us. Figure 6 displays thresholding utilising fundamental global thresholding.

F. Image Sharpning :

Any enhancing method known as image sharpening emphasises a picture's edges and small details. Increasing this setting results in a sharper image.

G. Highpass Filtering :

A picture can look crisper by using a high-pass filter.Thesefilters draw attention to the image's minute elements. Here, the thresholding output is provided as input. Here , we're using afilter , and to the pixels at the border pixels , first the closest values are added.

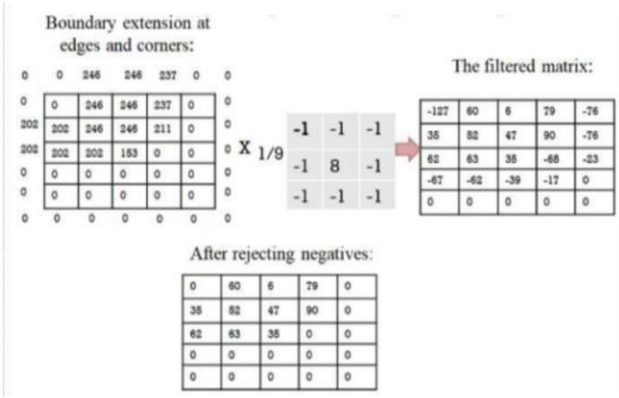

Fig. 7. Image sharpening using High - pass filtering

The value for a certain pixel location is obtained by multiplying the 3*3 input matrix's elements by the filter matrix

, which may be represented as A(1,1)*B(1,1).All of the 3*3 input matrix's components are so multiplied , and their sum is divided by 9, giving the result. The values of each pixel pointare determined in the same manner. Since there is no such thing as negative lighting , the negative values are taken to bezero.

H. Feature extraction using HOG :

A dimensionality reduction technique called feature extraction divides a large amount of raw data into smaller , easier to process groupings. To extract the features from the preprocessed picture received as input, a technique known as Histogram Orientation Gradient (HOG) is employed.It entailsseveral processes, such as determining Gx and Gy, which are gradients around each pixel in the x and y axes. The magnitude and gradient of the pixel's orientation are then calculated using applicable formulas. The angles and frequencies are then displayed to make a histogram, which is the module's output.

I. Classification using Convolutional Neural Networks :

Convolutional neural networks are a family of deep neuralnetworks that are frequently used to analyse visual vision in deep learning. As a result of its shared weights design and translation invariance properties , they are often referred to as shift invariant or space invariant artificial neural networks It is not needed to do feature extraction when CNN is employedfor classification. CNN will also do feature extraction. If a face is present , the preprocessed image is directly sent into CNN's classifier to determine its kind. By taking into accountall the characteristics in the output layer , a result with some predictive value is produced. Through the use of the SoftMaxactivation function , these values are determined.

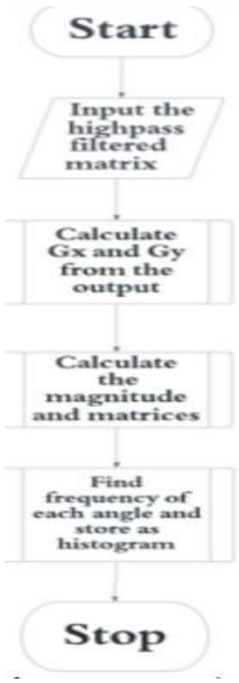

Fig. 8. Flow chart for Feature extraction

J. Gx and Gy in HOG :

Figure 9 depicts the feature extraction process using HOG. Magnitude represents illumination , and degree represents angle of orientation. Following the calculation of the the orientation angle , the frequency of the angles for the specific intervals are documented and provided as input to the classifier. Here , zeroes are not taken into account while calculating frequency. For instance , the frequency is written as 2 since there are two occurences for the range of 40 to 59.

Magnitude=√[Gx²+Gv²]
Ø=ta =Tan⁻¹(Gy/Gx)

Magnitude:

69.5	52.3	50.7	90.2	79.0
80.9	12.4	47.8	91.9	90.0
72.0	58.6	78.0	96.6	0
62.0	63.0	35.0	0	0
0	0	0	0	0

Ø:

30.25	83.42	67.99	86.19	0
50.01	14.04	37.34	59.25	0
29.05	62.56	36.72	68.74	0
0	0	0	0	0
0	0	0	0	0

f	1	4	2	3	2	0	0	0	0	0
Bin	0	20	40	60	80	100	120	140	160	180

Fig. 9. Feature extraction using HOG

K. Convolutional Layer :

The first stage of CNN is the Convolutional Layer, which takes 3*3 of the supplied matrix derived from the High-pass filter as input. This 3*3 matrix is multiplied by the filter matrix for the appropriate position, and the sum is printed in the position. This is seen in the image below. This output is sent to the pooling layer, which further reduces the matrix. The Convolutional Layer is seen in Figure 10,11 and 12

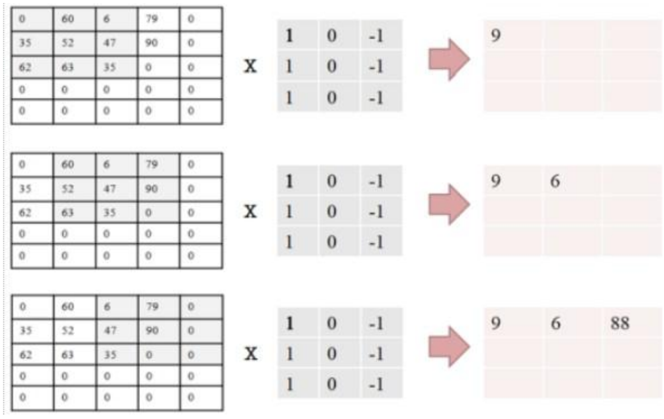

Fig. 10. Convolutional Neural Network Input matrix

Before pooling, convolution is followed by rectification of negative values to 0s. It is not provable in this case since all values are positive. Before pooling, numerous repetitions of both are required.

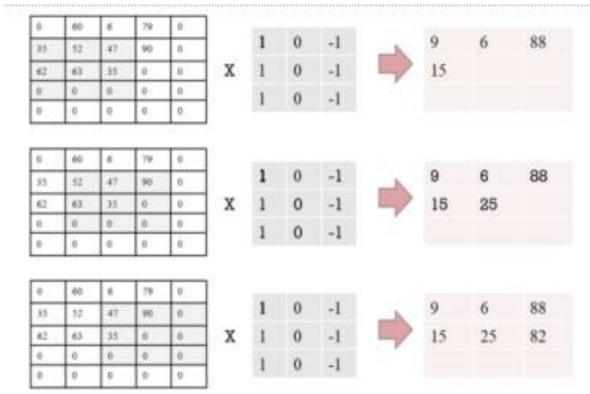

Fig. 11. Convolutional Neural Network Input matrix

L. Pooling Layer :

In the Pooling layer, a 3*3 matrix is reduced to a 2*2 matrix by picking the maximum of the particular 2*2 matrix at a specific point. The Pooling Layer is seen in Figure 13

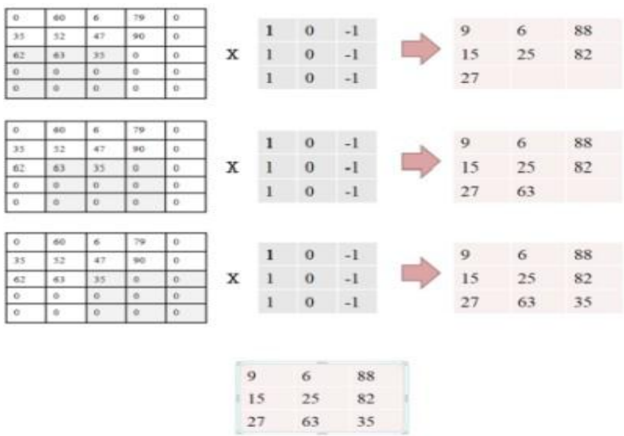

Fig. 12. Convolutional Neural Network output matrix

M. Fully connected layer and Output Layer :

The pooling layer's output is flattened, and this flattened matrix is passed into the Fully Connected Layer. There are numerous layers in the fully linked layer, including the Input layer, Hidden layer, and Output layer. The result is then passed into the classifier, which in this case uses the SoftMax Activation Function to determine whether or not a face is present in the image. The Fully linked layer and Output Layerare depicted in Figures 14 and 15.

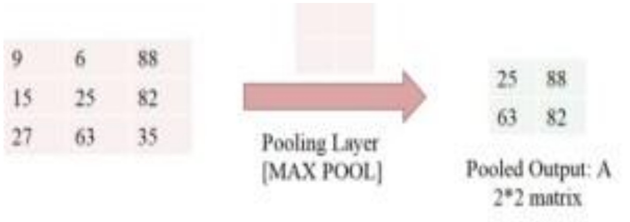

Fig. 13. Pooling layer

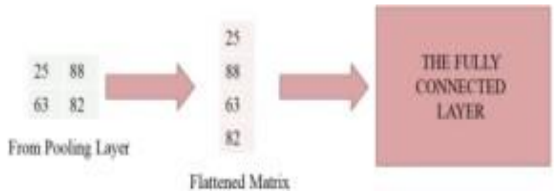

Fig. 14. The Fully connected Layer

The picture is pre-processed by converting the RGB to grayscale image and feature extraction is performed by the neural network's first layer, which is the convolution layer, anddetection is performed by employing fully connected layers ofthe convolutional neural network.

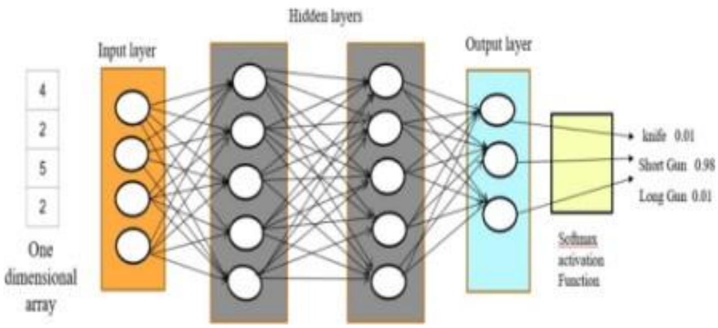

Fig. 15. The Fully connected Output Layer

N. The Caffe Framework :

One of the most widely utilised methodologies in current Artificial Intelligence is neural network (NN) technology (AI).It has been used to solve issues like as forecasting, adaptive control, recognising categorization, and many more. An artificial neural network (NN) is a simplified representationof a biological brain. It is made up of components known as neurons. An artificial neuron is just a mathematical representation of a biological neuron. Because an artificial neural network is based on the real brain, it shares conceptual features such as the ability to learn. Convolutional Neural Networks (CNN) and Deep Learning (DL) are new developments in the field of NN computing. CNN is a neural network with a unique structure that was created to mimic a human visual system (HVS). Thus, CNNs are best suited for handling computer vision issues like as object identification and image and video data categorization. They've also been employed for speech recognition and text translation with success. The growing popularity of deep learning technology has spurred the creation of several new CNN programming frameworks.

Caffe, TensorFlow, Theano, Torch, and Keras are the most popular frameworks.Convolutional neural networks differ from other neural networks in that they function better with picture, voice, or audio signal inputs. They have three different sorts of layers:

1. Convolutional layer
2. Pooling layer
3. Fully-connected (FC) layer

A convolutional network's initial layer is the convolutional layer. While convolutional layers can be followed by other convolutional layers or pooling layers, the last layer is the fully-connected layer. The CNN becomes more complicated with each layer, detecting more areas of the picture. Earlier layers concentrate on fundamental aspects like colours and borders. As the visual data travels through the CNN layers,it begins to distinguish bigger components or features of the item, eventually identifying the target object.

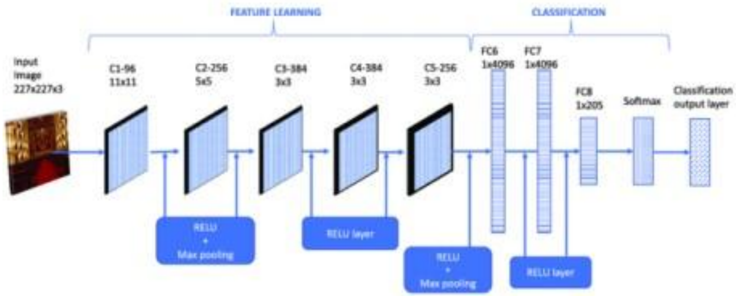

Fig. 16. CNN architecture diagram

O. Training a CNN using CAFFE in 4 steps :

1. Data preparation : In this step , the images are cleaned and stored in a format that can be used by caffe. A python script that will handle both image preprocessing and storage.
2. Model definition : In this step , a CNN architecture was chosen and its parameters are defined in a configuration file with extension .protxt
3. Solver definition : The solver is responsible for model optimization. The solver parameters are defined in a configuration file with extension .protxt
4. Model Training : the model is trained by executing one caffe command from the terminal. After training the model , the trained model in a file with extension. caffemodel is found.

ANALYSIS RESULT

P. Accuracy parameters :

Although the gender prediction network worked well , our expectations were not met by the age prediction network. Theconfusion matrix for the age prediction model is what we found when searching the paper for the solution.

The graph in figure 17 allows for the following observations to be made : The prediction accuracy for the age ranges 0-2,4-6,8-13, and 25-32 is quite high. The results are strongly skewed toward the 25-32 age group.

This indicates that it is quite simple for the network to mix up the ages of 15 and 43. Therefore , there is a good possibility that the anticipated age will be between 25 and 32

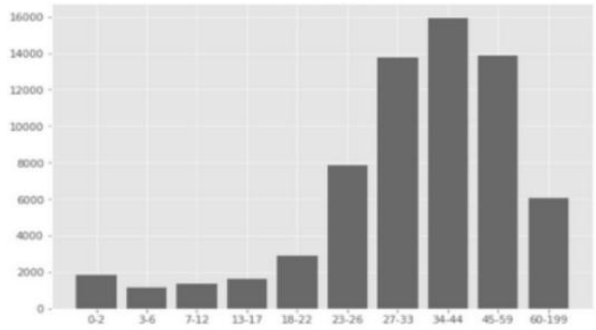

Fig. 17. Dataset results bin wise

, even if the real age is between 15-20 or 38 and 43. The results section further supports this. In addition ,it was found that padding around the identified case increased the model'saccuracy. This could be because standard face photos were used as training input instead of the closely cropped faces obtained after face detection. This project also examines the usage of face alignment prior to prediction and discovered that while it became better for some cases , it got worse for others.If you work with non-frontal faces most of the time , using alignment could be a smart option

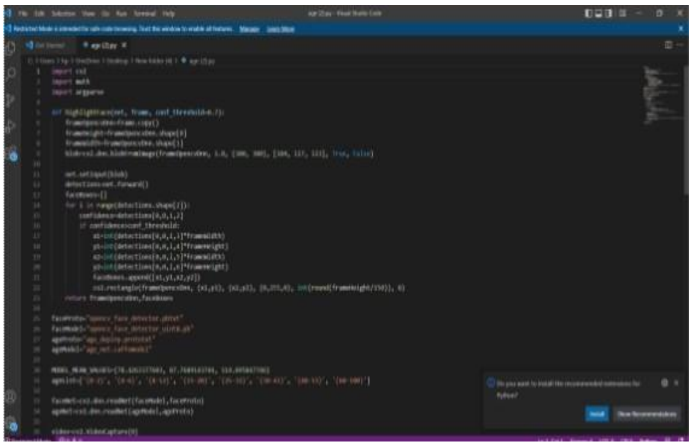

Fig. 18. Code snapshot for age and gender detection

Fig. 19. Result snapshots using Raspberry pi setup

FUTURE SCOPE

The Fucture scope of the project are:-

1. In order to make the project more accessible, it might beturned into a web application or a mobile application.
2. In the future, It may be improved such that it can determine the age and gender of a group of people in theimage.

CONCLUSION

The project titled Vehicle Driver Age Estimation Using Neural Network aims to predict the age and gender of the people accurately. The first objective of the project was to detect and extract the facial region from the input image fed by the camera. The second objective was to select the frontal face image from the extracted facial region usinghead pose estimation. The third objective was to pretrain the convolutional neural network model and preprocess the images from the input data. The final objective was to develop a convolutional neural network using caffe frameworkto assess the driver's age with the best accuracy values. To provide a varied dataset for pre-training the CNN for facial recognition, a sizable face dataset with a wide age range was compiled from several sources. Approximately 22,000 photos were acquired from UTK, while roughly 38,000 were taken from IMDB, creating a sizable aggregated data set. After deployment, the CNN model created for the project was able to recognise faces and gender with an accuracy of about

98.1 percent. OpenCV's age and gender detection will be very helpful for driver's age and gender estimation. When coupled, CNN and OpenCV can produce excellent results. The project's UTK and IMDB dataset collection produces results with improved precision. As pre-trained models, the caffe model files are utilised. This project demonstrated how face detection using OpenCV may be done without the use ofany extra expensive procedures.

ACKNOWLEDGMENT

We would like to thank our project mentor Prof.Rajithkumar B K for guiding us in successfully completing this project. She helped us with her valuable suggestions on techniques and methods to be used in completion for the project. We would also like to thanks to our college and the Head of Department Dr. H V Ravish Aradhya for allowing usto choose this topic

REFERENCES

1. Verma, U. Marhatta, S. Sharma, and V. Kumar, "Age prediction using image dataset using machine learning," International Journal of Innovative Technology and Exploring Engineering, vol. 8, pp. 107–113, 2020
2. R.Iga, K. Izumi, H. Hayashi, G. Fukano, and T. Ohtani,A gender and age estimation system from face images, IEEE, 2003.
3. J. Marquardt, G. Farnadi, G. Vasudevan, et al., Age andgender identification in social media, 2014
4. A. M. Abu Nada, E. Alajrami, A. A. Al-Saqqa, and S. S. Abu-Naser, "Age and gender prediction and validation through single user images using cnn," 2020.
5. I. Rafique, A. Hamid, S. Naseer, M. Asad, M. Awais, and T. Yasir, Age and gender prediction using deep convolutional neural networks, IEEE, 2019.
6. M. A. Alvarez-Carmona, L. Pellegrin, M. Montes-y G´omez, et al., A visual approach for age and gender identification on twitter, 2018.
7. A. Abdolrashidi, M. Minaei, E. Azimi, and S. Minaee, Age and gender prediction from face images using attentional convolutional network, 2020.
8. M. Dileep and A. Danti, Human age and gender prediction based on neural networks and three sigma control limits, 2018.
9. Razalli and M. H. Alkawaz, Real-time face tracking application with embedded facial age range estimation algorithm, IEEE, 2019.
10. A. Salihbaˇsi´c and T. Orehovaˇcki, Development of android application for gender, age and face recognition using opencv, IEEE, 2019.
11. T. R. Kalansuriya and A. T. Dharmaratne, Neural network based age and gender classification for facial images, 2014.
12. Biradar, B. Torgal, N. Hosamani, R. Bidarakundi, and S. Mudhol, Age and gender detection system using raspberry pi, 2019.

13. Liao, Y. Yan, W. Dai, and P. Fan, Age estimation of face images based on cnn and divide-and-rule strategy, 2018.

14. M. Duan, K. Li, C. Yang, and K. Li, A hybrid deep learning cnn–elm for age and gender classification, 2018.

15. Azarmehr, R. Laganiere, W.-S. Lee, C. Xu, and D. Laroche, Real-time embedded age and gender classification in unconstrained video, 2015.

16. Verma, U. Marhatta, S. Sharma, and V. Kumar, Age prediction using image dataset using machine learning, 2020

17. M. Duan, K. Li, C. Yang, and K. Li, "A hybrid deep learning cnn–elm for age and gender classification,"Neurocomputing, vol. 275, pp. 448–461, 2018

18. Levi and T. Hassner, "Age and gender classification using convolutional neural networks," in Proceedings of the IEEE conference on computer vision and pattern recognition workshops, 2015, pp. 34–42.