AGE & GENDER CLASSIFICATION USING DIFFERENT ALGORTHIM'S

A Project Report

submitted in the partial fulfilment of the requirement

for the award of the degree of

BACHELOR OF TECHNOLOGY

In

ELECTRONICS AND COMMUNICATION ENGINEERING

By

BATCH NO : 18IEDCMP11

DALALI ARIF - 180040165

B.NIKHIL VISHNU - 180040454

I.NARENDRA DATTA - 180040736

Under the supervision of

Dr.P.LAKSHMAN

(Associate Professor, Department of ECE)

(DEEMED TO BE UNIVERSITY)

Koneru Lakshmaiah Education Foundation

(Deemed to be University estd., u/s 3 of UGC Act 1956)

Greenfields, Vaddeswaram, Guntur (Dist.), Andhra Pradesh - 522502

2022

Age and Gender Classification using Different Algorithm's

Project Report

Submitted in the partial fulfillment of the requirements for

the award of the degree of

Bachelor of Technology

In

Department of Electronics and Communication Engineering

By

Batch - 18IEDCMP11

Dalali Arif	**180040165**
B. Nikhil Vishnu	**180040454**
I. Narendra Datta	**180040736**

Under the esteemed guidance of

Dr.P. Lakshman

ASSOC.PROFESSOR/DEPT.HOD

ECE DEPARTMENT

(DEEMED TO BE UNIVERSITY)

Koneru Lakshmaiah Education Foundation

(Deemed to be University estd., u/s 3 of UGC Act 1956)

Greenfields, Vaddeswaram, Guntur (Dist.), Andhra Pradesh - 522502

KONERU LAKSHMAIAH EDUCATIONAL FOUNDATION
DEPARTMENT OF ELECTRONICS AND COMMUNICATION ENGINEERING

DECLARATION

The Project Report entitled "**Age and Gender Classification using Different Algorithm's**" is a record of bonafide work of Dalali Arif -180040165, B. Nikhil Vishnu - 180040454, I. Narendra Datta - 180040736 submitted in partial fulfilment for the award of B. Tech in Electronics and Communication Engineering to the K L University. The results embodied in this report has not been copied from any other departments/University/Institute.

NAME	ID NUMBER
Dalali Arif	**180040165**
B. Nikhil Vishnu	**180040454**
I. Narendra Datta	**180040736**

DEPARTMENT OF ELECTRONICS AND COMMUNICATIONS ENGINEERING

CERTIFICATE

This is to certify that the Project Report entitled "**Age and Gender Classification using Different Algorithm's**" is being submitted by Dalali Arif -180040165, B. Nikhil Vishnu -180040454, I. Narendra Datta - 180040736 submitted in partial fulfilment for the award of B. Tech in Electronics and Communication Engineering to the KL University is a record of bonafide work carried out under our guidance and supervision. The results embodied in this report have not been copied from any other departments/ University/Institute.

Signature of the Supervisor
Dr. P. Lakshman

Signature of the HOD
Dr. Suman Maloji

Signature of the External Examiner

ACKNOWLEDGEMENT

It is great pleasure for me to express my gratitude to our honorable President Sri. **Koneru Satya Narayana**, for giving the opportunity and platform with facilities in accomplishing the project**-based** laboratory report.

We express sincere gratitude to our principal **Dr. K. Subba Rao** for his administration towards our academic growth.

We record it as my privilege to deeply thank our pioneer Prof. **Dr. M. Suman** HOD-ECE and **Dr. P. Lakshman** our project guide for providing us the valuable support to make our ideas into reality.

We express my sincere thanks to our project supervisor for her novel association of ideas, encouragement, appreciation, and intellectual zeal which motivated us to venture into this project successfully.

Finally, it is pleased to acknowledge the indebtedness to all those who devoted themselves directly or indirectly to make this project report success.

Place: KLEF, Vijayawada.

NAME	**ID NUMBER**
Dalali Arif	**180040165**
B. Nikhil Vishnu	**180040454**
I. Narendra Datta	**180040736**

TABLE OF CONTENTS

LIST OF FIGURE’S

LIST OF TABLE’S

1. ABSTRACT

This paper focuses on the problem of gender and age classification for an image. I build off of previous work that has developed efficient, accurate architectures for these tasks and aim to extend their approaches in order to improve results. The first main area of experimentation in this project is modifying some previously published, effective architectures used for gender and age classification. My attempts include reducing the number of parameters (in the style of), increasing the depth of the network, and modifying the level of dropout used. These modifications ended up causing system performance to decrease (or at best, stay the same) as compared with the simpler architecture I began with. This verified suspicions I had that the tasks of age and gender classification are more prone to over-fitting than other types of classification. The next facet of my project focuses on coupling the architectures for age and gender recognition to take advantage of the gender-specific age characteristics and age specific gender characteristics inherent to images. This stemmed from the observation that gender classification is an inherently easier task than age classification, due to both the fewer number of potential classes and the more prominent intra-gender facial variations. By training different age classifiers for each gender, I found that I could improve the performance of age classification, although gender classification did not see any significant gains.

Gender recognition of a person is an important and difficult field in image processing. Computerized gender acknowledgement is a inspiring field where researches are been taking place. This research work has been used in variety of real time applications .These include intelligent surveillance ,interaction between humans and robots , behavior analysis of people, sum up number of males and females in a public place. Previous research works were not up to the mark as they have less accuracies in identifying the gender of a pedestrian. In this paper we have proposed a gender identification model through body appearance. The training and testing is performed on MIT dataset that contains both front and back views of a pedestrian. For classification purpose we used CNN algorithm on **Mall_Customers** dataset and this approach has achieved an accuracy of 97.5 percentage.

2. INTRODUCTION

The aim is to predict the age of individuals using image data sets. An growing number of applications, especially after the increase in social networks and social media, are being concerned with automatic age classification. Age and gender are the two most fundamental facial qualities in social interaction. In smart applications, such as access control, human computer interaction, enforcement, marketing intelligence and visual supervision, etc, it is important to make age evaluations using one facial image. Machine learning: supervised learning, image recognition, and deep learning: a ground-breaking neural network and profound learning are the most common technologies used in this project. Supervised learning can be described as a machine learning technique in which the input is mapped to the output using input-output pair training data. TensorFlow is an open-source library used for math, data flow and specific machine learning applications.

Convolutional Neural Network (CNN) is one of the most prevalent algorithms that has gained a high reputation in image feature extraction. Age Classification using Convolutional Neural Networks: A Convolutionary Neural Network (ConvNet / CNN) is a Deep Learning algorithm, which allows an input image to take on different aspects / objects and can be distinguished from one image (learnable weights and biases). ConvNet requires much less preprocessing than other classification algorithms. While the filters are hand-made in primitive methods, ConvNets can learn these filters / features with adequate training. The ConvNet architecture is similar to that of neurons in the human brain and was influenced by the Visual Cortex organisation. Within a limited area of the visual field known as the Receptive Field, only individual neurons respond to stimuli. The entire visual area is protected by a selection of these fields. About Dataset: a broad facial dataset of long age (range 0-116 years old) is a UTKFace data set. The data collection consists of more than 20,000 facial images with age, gender and ethnicity annotations. The images cover a wide range of poses, facial expression, lighting, occlusion, resolution. It can be used for a variety of tasks, for example face detection, age estimation, age progression, position of landmarks etc. The survey is focused on the age detection of the neural network (CNN) image dataset architecture. The problem may then be treated as a classification concern with 3 convolution layers and 2 completely interconnected layers with a final output layer. Estimating the exact age by regression is a challenging process. Age prediction systems have been growing rapidly in recent days thanks to its important modules and use for many computer vision applications, such as interaction between human and computer, safety systems and visual monitoring. The value of an age prediction is shown by several examples. For example, there is an age to get alcohol, drive vehicles, travel alone outside the country, smoke cigarettes, etc. The problem is, however, that human capacities are poor and unreliable in age prediction. So, it would be necessary to reject underage individuals with computer vision systems. Hotels, airports, busses, casinos, government buildings, universities , hospitals, movie theatres, etc. are currently using automated age and gender prediction systems for improving protection and mitigating possible threats or poverty. Age prediction methods are also used in healthcare systems, knowledge recovery, academic studies, and Electronic Customer Relationship Management (ECRM) applications, which distributes customers to a range of aged groups including teenagers, teens, adults and senior citizens.

Moreover, it may allow businesses to identify products and services according to their age groups that increase income and make more money to collect those customers' daily lives information including behaviours, preferences, practices, 4 priorities etc. For instance, clothing shops that sell men's or women's fashion according to their age groups; restaurants wish to know the most common meals per group of age; many businesses want those Mall-Customers to advertise according to their age groups.

3. LITERATURE REVIEW

A new architecture for face image classification named unsupervised CNN was introduced by S. U. Rehman et al. [2]. A CNN that handles multitask (i.e. Facial detection and emotional classification) is made by merging CNN with other modules and algorithms. A hybrid deep CNN and RNN (Recurrent Neural Network) model was introduced by N. Jain et al. [4]. This model aims to improve the overall result of face detection. MI Facial Expression and JAFFE dataset were used to evaluate the model. A convolutional network architecture was proposed by G. Levi et al. [5] that classified the age with small amounts of data. The Mall-Customer Benchmark was used to train the model. A system in which a real time automatic facial expression system was designed was proposed by S. Turabzadeh et al. [6]. It was implemented and tested on an embedded device which could be the first step for a specific facial expression recognition chip for a social robot. MATLAB was first used to build and simulate the system and then it was built on an embedded system. The hardship of performing automatic prediction of age, gender and ethnicity on the East Asian Population using a Convolutional Neural Network (CNN) was explored by N. Srinivas et al. [3]. A fine-grained ethnicity has predictions based on a refined categorization of the human population (Chinese, Japanese, Korean, etc.). Previous results suggest that the most critical job is to predict the fine-grained ethnicity of a person, followed by age and lastly gender. An automated recognition system for age, gender and emotion was presented by A. Dehghan et al. [7] that was trained using deep neural network. At the ImageNet LSVRC-2010 contest, A. Krizhevskyetal. [8] presented a paper which suggested segregation of 1.2 million images into 1000 different categories with the help of a deep Convolutional neural network. The results which were obtained suggested that supervised learning can deliver exceptional accuracies. Some datasets have annotations on the face images which are not considered to be of any use for face recognition. Some papers have also used RNN but it is not applicable for our project as the RNN takes text or speech as an input whereas we required an image to be as the input. Hence, CNN is chosen over RNN for the sake of our project. Some papers also suggest the use of unsupervised CNN, but, for this project supervised learning is more appropriate. The UTKFace dataset is used as dataset for the project.

- A hybrid deep learning CNN–ELM for age and gender classification Automatic age and gender classification has been widely used in a large amount of applications, particularly in human-computer interaction, biometrics, visual surveillance, electronic customer, and commercial applications. In this paper, we introduce a hybrid structure which includes Convolutional Neural Network (CNN) and Extreme Learning Machine (ELM), and integrates the synergy of two classifiers to deal with age and gender classification. The hybrid architecture makes the most of their advantages: CNN is used to extract the features from the input images while ELM classifies the intermediate results. We not only give the detailed deployment of our structure including design of parameters and layers, analysis of the hybrid architecture, and the derivation of back-propagation in this system during the iterations, but also adopt several measures to limit the risk of overfitting. After that, two popular datasets, such as, MORPH-II and Mall-Customer Benchmark, are used to verify our hybrid structure. Experimental results show that our hybrid architecture 4 outperforms other studies on the same datasets by exhibiting significant performance improvement in terms of accuracy and efficiency. • Age and gender classification from speech and face images by jointly fine-tuned deep neural networks The classification of human's age and gender from speech and face images is a challenging task that has important applications in real-life and its applications are expected to grow more in the future. Deep neural networks (DNNs) and Convolutional neural networks (CNNs) are considered as one of the state-of-art systems as feature extractors and classifiers and are proven to be very efficient in analysing problems with complex feature space. In this work, we propose a new cost function for fine-tuning two DNNs jointly. The proposed cost function is evaluated by using speech utterances and unconstrained face images for age and gender classification task. The proposed classifier design consists of two DNNs trained on different feature sets, which are extracted from the same input data. Melfrequency cepstral coefficients (MFCCs) and fundamental frequency (F0) and the shifted delta cepstral coefficients (SDC) are extracted from speech as the first and second feature sets, respectively. Facial appearance and the depth information are extracted from face images as the first and second feature sets, respectively. Jointly training of two DNNs with the proposed cost function improved the classification accuracies and minimized the over-fitting effect for both speech-based and imagebased systems. Extensive experiments have been conducted to evaluate the performance and the accuracy of the proposed work. Two publicly available databases, the Age-Annotated Database of the German Telephone Speech database (a Gender) and the Mall-customer database, are used to evaluate the proposed system. The overall accuracy of the proposed system is calculated as 56.06% for seven speaker classes and overall exact accuracy is calculated as 63.78% for Mall-Customer database. • Local Deep Neural Networks for Age and Gender Classification Local deep neural networks have been recently introduced for gender recognition. Although, they achieve very good performance they are very computationally expensive to train. In this work, we introduce a simplified version of local deep neural networks which significantly reduces the training time. Instead of using hundreds of patches per image, as suggested by the original method, we propose to 5 use 9 overlapping patches per image which cover the entire face region. This results in a much reduced training time, since just 9 patches are extracted per image instead of hundreds, at the expense of a slightly reduced performance. We tested the proposed modified local deep neural networks approach on the LFW and Mall-Customer databases for the task of gender and age classification. For both tasks and both databases the performance is up to 1% lower compared to the original version of the algorithm. We have also investigated which patches are more discriminative for age and gender classification. It turns out that the mouth and eyes regions are useful for age classification, whereas just the eye region is useful for gender classification. • Age and gender classification using brain–computer interface with the development of Internet of things (IOT), it is now possible to connect various heterogeneous devices together using Internet. The devices are able to share their information for various applications including health care, security and monitoring. IOT facilitates patients to self-monitor their physiological states invariably and doctors to monitor their patients remotely. Electroencephalography (EEG) provides a monitoring method to record such electrical activities of the brain using sensors. In this paper, we present an automatic age and gender prediction framework of users based on their neurosignals captured during eyes closed resting state using EEG sensor. Using EEG sensor, brain activities of 60 individuals with different age groups varying between 6 and 55 years and gender (i.e., male and female) have been recorded using a wireless EEG sensor. Discrete wavelet transform frequency decomposition has been performed for feature extraction. Next, random forest classifier has been applied for modelling the brain signals. Lastly, the accuracies have been compared with support vector machine and artificial neural network classifiers. The performance of the system has been tested using userindependent approach with an accuracy of 88.33 and 96.66% in age and gender prediction, respectively. It has been analysed that oscillations in beta and theta band waves show maximum age prediction, whereas delta rhythm leads to highest gender classification rates. The proposed method can be extended to different IOT applications in healthcare sector where age and gender information can be automatically transmitted to hospitals and clinics through Internet. • Age and gender recognition in the wild with deep attention Face analysis in images in the wild still pose a challenge for automatic age and 6 gender recognition tasks, mainly due to their high variability in resolution, deformation, and occlusion. Although the performance has highly increased thanks to Convolutional Neural Networks (CNNs), it is still far from optimal when compared to other image recognition tasks, mainly because of the high sensitiveness of CNNs to facial variations. In this paper, inspired by biology and the recent success of attention mechanisms on visual question answering and fine-grained recognition, we propose a novel feedforward attention mechanism that is able to discover the most informative and reliable parts of a given face for improving age and gender classification. In particular, given a down sampled facial image, the proposed model is trained based on a novel end-to-end learning framework to extract the most discriminative patches from the original high-resolution image. Experimental validation on the standard Mall-Customer, Images of Groups, and MORPH II benchmarks shows that including attention mechanisms enhances the performance of CNNs in terms of robustness and accuracy.

Related Work: We briefly review related tactics for age and gender orientation arrangement before presenting the proposed strategy, as well as a concise explanation of profound convolution organisations In this project I used colab which is popularly know as Online python tool. Colab is a free notebook environment that runs entirely in the cloud. It lets you and your team members edit documents, the way you work with Google Docs. Colab supports many popular machine learning libraries which can be easily loaded in your notebook. Google is quite aggressive in AI research. Over many years, Google developed AI framework called TensorFlow and a development tool called Colaboratory. Today TensorFlow is open-sourced and since 2017, Google made Colaboratory free for public use. Colaboratory is now known as Google Colab or simply Colab. Another attractive feature that Google offers to the developers is the use of GPU. Colab supports GPU and it is totally free. The reasons for making it free for public could be to make its software a standard in the academics for teaching machine learning and data science. It may also have a long term perspective of building a customer base for Google Cloud APIs which are sold per-use basis. 7 Irrespective of the reasons, the introduction of Colab has eased the learning and development of machine learning applications. Yes, There are many reasons for using Google çolab some of them are it provide free computational power, Your code is executed in a virtual machine dedicated to your them are it provides free account, Even better thing is you are able to use a GPU accelerator in your projects even better all this can be done by a simple click, Powered by a Tesla K80 CPC gives you 12GB of free RAM and you will be able to use this for upto 12 hours. As free as it is everything has limitations so does colab. It was invented for interactive use, Somethings are unsupported such as cryptocurrency mining and long running background computational tasks are also not so welcome. In such cases we can use local runtime option. Grouping up the main reasons for opting are

1.No set up required

2.Many Libraries are available

3.Easy sharing

4.Supports both python 2.7 and python 3.6

5.It is also integrated with Github

As a programmer, you can perform the following using Google Colab.

- Write and execute code in Python

- Document your code that supports mathematical equations
- Create/Upload/Share notebooks
- Import/Save notebooks from/to Google Drive
- Import/Publish notebooks from GitHub
- Import external datasets e.g. from Kaggle
- Integrate PyTorch, TensorFlow, Keras, OpenCV
- Free Cloud service with free GPU

LIMITATIONS

- When compared with the existing work, the accuracy values of the classifier are low.
- To predict the pedestrian based on the appearance is complicated due to large variation of appearance, poses and background clutter.
- Inaccurate prediction of pedestrian.

4. PROGRAMMING LANGUAGE

In this project I have used python programming. Python is a general purpose, dynamic, high-level, and interpreted programming language. It supports Object Oriented programming approach to develop applications. It is simple and easy to learn and provides lots of high-level data structures. Python is easy to learn yet powerful and versatile scripting language, which makes it attractive for Application Development. Python's syntax and dynamic typing with its interpreted nature make it an ideal language for scripting and rapid application development. Python supports multiple programming pattern, including object-oriented, imperative, and functional or procedural programming styles. Python is not intended to work in a particular area, such as web programming. That is why it is known as multipurpose programming language because it can be used with web, enterprise, 3D CAD, etc. We don't need to use data types to declare variable because it is dynamically typed so we can write a=10 to assign an integer value in an integer variable. Python makes the development and debugging fast because there is no compilation step included in Python development, and edit-test-debug cycle is very fast. 4.2

Python Features:

1) Easy to Learn and Use
2) Expressive Language
3) Interpreted Language
4) Cross-platform Language
5) Free and Open Source
6) Extensible

5.THEORETICAL ANALYSIS

5.1 Dataset:

For this python project, I had used the **Mall_Customers** dataset; the dataset is available in the public domain .

This data set is created only for the learning purpose of the customer segmentation concepts , also known as market basket analysis . I will demonstrate this by using unsupervised ML technique (KMeans Clustering Algorithm) in the simplest form.

You are owing a supermarket mall and through membership cards , you have some basic data about your customers like Customer ID, age, gender, annual income and spending score.
Spending Score is something you assign to the customer based on your defined parameters like customer behavior and purchasing data.

ProblemStatement
You own the mall and want to understand the customers like who can be easily converge [Target Customers] so that the sense can be given to marketing team and plan the strategy accordingly.

1	CustomerID	Gender	Age	Annual Income (k$)	Spending Score (1-100)
2	1	Male	19	15	39
3	2	Male	21	15	81
4	3	Female	20	16	6
5	4	Female	23	16	77
6	5	Female	31	17	40
7	6	Female	22	17	76
8	7	Female	35	18	6
9	8	Female	23	18	94
10	9	Male	64	19	3
11	10	Female	30	19	72
12	11	Male	67	19	14
13	12	Female	35	19	99
14	13	Female	58	20	15
15	14	Female	24	20	77
16	15	Male	37	20	13
17	16	Male	22	20	79
18	17	Female	35	21	35
19	18	Male	20	21	66
20	19	Male	52	23	29

Fig:-1 Dataset of the mall customers

Here we have the following features :

1. CustomerID: It is the unique ID given to a customer
2. Gender: Gender of the customer
3. Age: The age of the customer
4. Annual Income(k$): It is the annual income of the customer
5. Spending Score: It is the score(out of 100) given to a customer by the mall authorities, based on the money spent and the behavior of the customer.

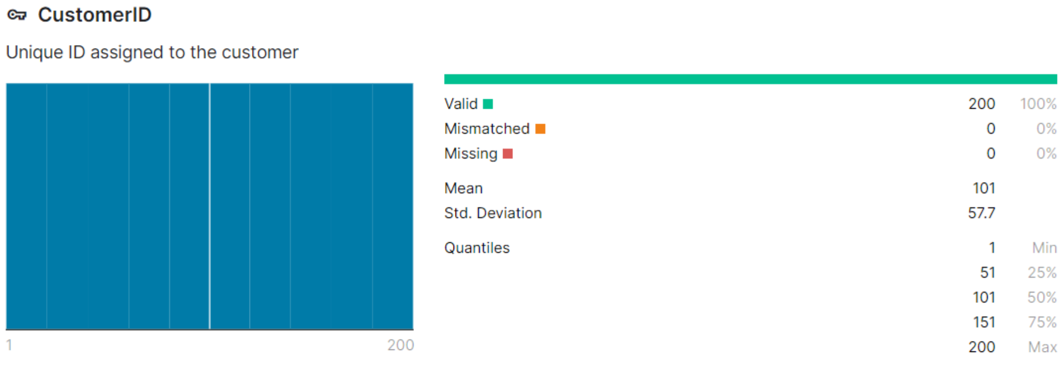


Fig:-2 CustomerID

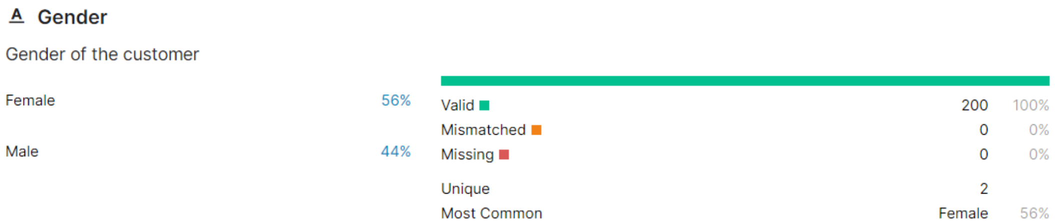


Fig:-3 Gender

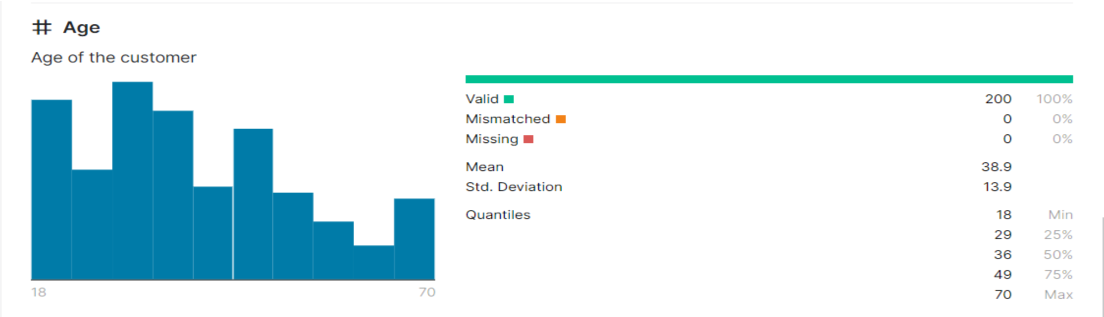


Fig:-4Age

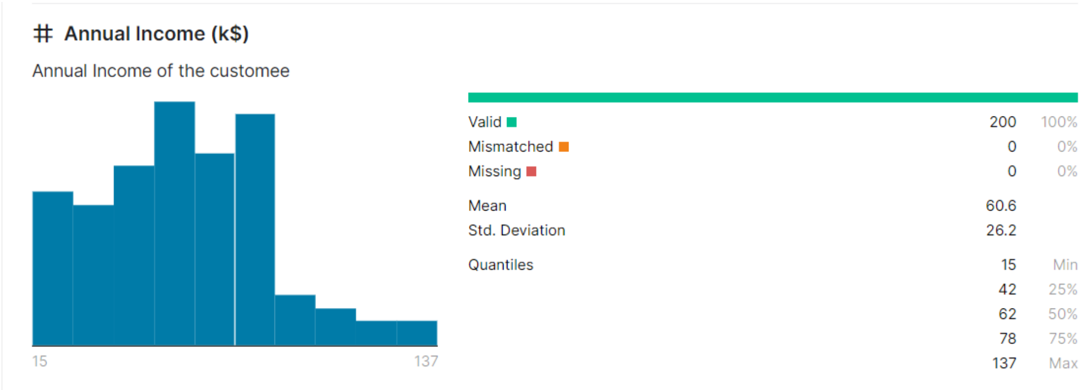


Fig:-5 Annual Income

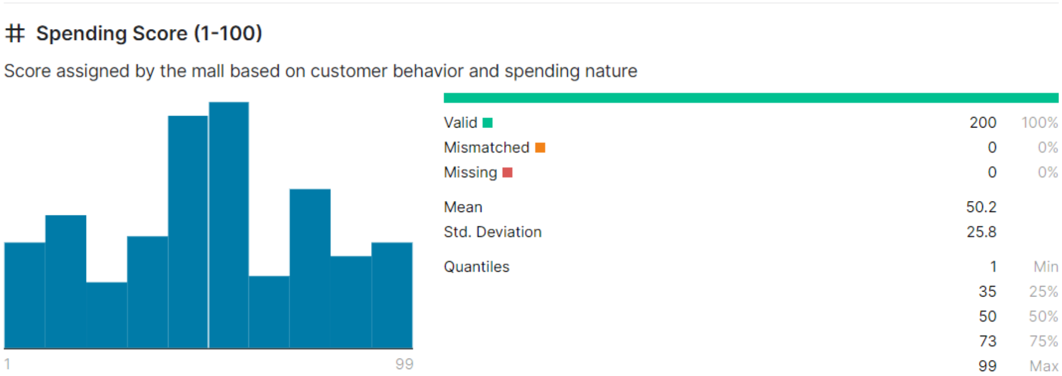


Fig:-6 Spending Score

5.2 Age classification:

Ideally, Age Prediction should be approached as a Regression problem since we are expecting a real number as the output. However, estimating age accurately using regression is challenging. Even humans cannot accurately predict the age based on looking at a person. However, we have an idea of whether they are in their 20s or in their 30s. Because of this reason, it is wise to frame this problem as a classification problem where we try to estimate the age group the person is in. For example, age in the range of 0-2 is a single class, 4-6 is another class and so on. Dataset has 8 classes divided into the following age groups [(0 – 2), (4 – 6), (8 – 12), (15 – 20), (25 – 32), (38 – 43), (48 – 53), (60 – 100)]. Thus, the age prediction network has 8 nodes in the final softmax layer indicating the mentioned age ranges. The problem of automatically extracting age related attributes from facial images has received increasing attention in recent years and many methods have been put fourth. A detailed survey of such methods can be found and, more recently. We note that despite our focus here on age group classification rather than precise age estimation (i.e., age regression), the survey below includes methods designed for either task. Early methods for age estimation are based on calculating ratios between different measurements of facial features . Once facial features (e.g. eyes, nose, mouth, chin, etc.) are localized and their sizes and distances measured, ratios between them are calculated and used for classifying the face into different age categories according to hand-crafted rules. More recently,uses a similar approach to model age progression in subjects under 18 years old. As those methods require accurate localization of facial features, a challenging problem by itself, they are unsuitable for in-the-wild images which one may expect to find on social platforms. On a different line of work are methods that represent the aging process as a subspace or a manifold A drawback of those methods is that they require input images to be near-frontal and well-aligned. These methods therefore present experimental results only on constrained data-sets of near-frontal images. Again, as a consequence, such methods are ill-suited for unconstrained images. Different from those described above are methods that use local features for representing face images. In Gaussian Mixture Models (GMM) were used to represent the distribution of facial patches. In GMM were used again for representing the distribution of local facial measurements, but robust descriptors were used instead of pixel patches. Finally, instead of GMM, Hidden-Markov Model, 12 super-vectors were used in for representing face patch distributions. An alternative to the local image intensity patches are robust image descriptors: Gabor image descriptors were used in along with a Fuzzy-LDA classifier which considers a face image as belonging to more than one age class. In a combination of BiologicallyInspired Features (BIF) and various manifold-learning methods were used for age estimation. Gabor and local binary patterns (LBP) features were used in along with a hierarchical age classifier composed of Support Vector Machines (SVM) to classify the input image to an age-class followed by a support vector regression to estimate a precise age. Finally, proposed improved versions of relevant component analysis and locally preserving projections . Those methods are used for distance learning and dimensionality reduction, respectively, with Active Appearance Models as an image feature. All of these methods have proven effective on small and/or constrained benchmarks for age estimation. To our knowledge, the best performing methods were demonstrated on the Group Photos benchmark . In state-of-the-art performance on this benchmark was presented by employing LBP descriptor variations and a dropout-SVM classifier. We show our proposed method to outperform the results they report on the more challenging Mall-Customer benchmark, designed for the same task.

5.3 Gender classification:

I have framed Gender Prediction as a classification problem. The output layer in the gender prediction network is of type softmax with 2 nodes indicating the two classes “Male” and “Female” A detailed survey of gender classification methods can be found in and more recently in . Here we quickly survey relevant methods. One of the early methods for gender classification used a neural network trained on a small set of near-frontal face images. In the combined 3D structure of the head (obtained using a laser scanner) and image intensities were used for classifying gender. SVM classifiers were used by , applied directly to image intensities. Rather than using SVM, used AdaBoost for the same purpose, here again, applied to image intensities. Finally, viewpointinvariant age and gender classification was presented by . . In , intensity, shape and texture features were used with mutual information, again obtaining near-perfect result.

5.4 CNN (Convolutional Neural Network)

Convolutional Neural Network is one of the main categories to do image classification and image recognition in neural networks. Scene labeling, objects detections, and face recognition, etc., are some of the areas where convolutional neural networks are widely used.

CNN takes an image as input, which is classified and process under a certain category such as dog, cat, lion, tiger, etc. The computer sees an image as an array of pixels and depends on the resolution of the image. Based on image resolution, it will see as h * w * d, where h= height w= width and d= dimension. For example, An RGB image is 6 * 6 * 3 array of the matrix, and the grayscale image is 4 * 4 * 1 array of the matrix.

In CNN, each input image will pass through a sequence of convolution layers along with pooling, fully connected layers, filters (Also known as kernels). After that, we will apply the Soft-max function to classify an object with probabilistic values 0 and 1.

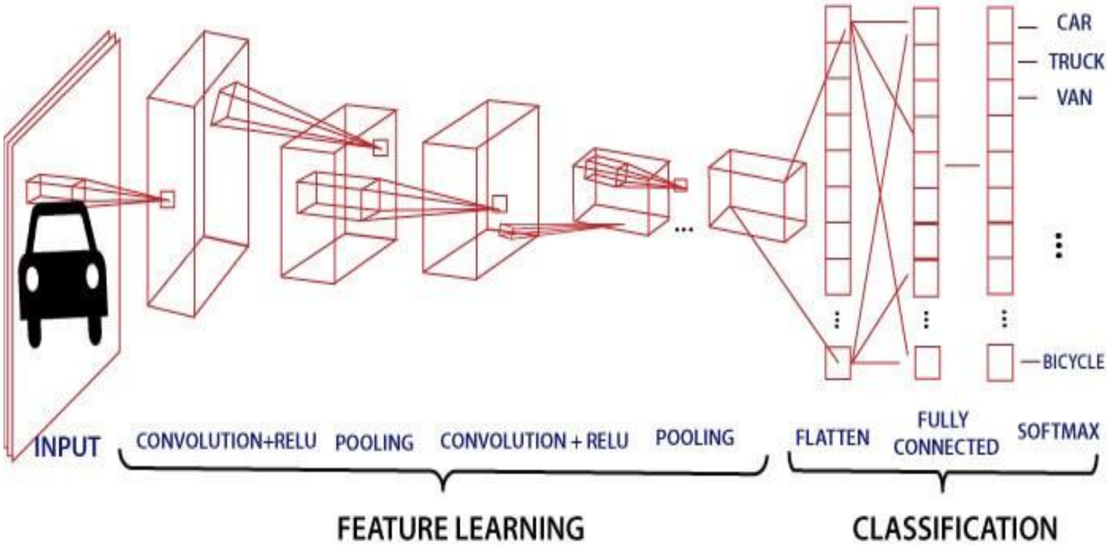


Fig:-7 CNN (Convolutional Neural Network)

5.5 K-Nearest Neighbour (KNN):-

- K-Nearest Neighbour is one of the simplest Machine Learning algorithms based on Supervised Learning technique.
- K-NN algorithm assumes the similarity between the new case/data and available cases and put the new case into the category that is most similar to the available categories.
- K-NN algorithm stores all the available data and classifies a new data point based on the similarity. This means when new data appears then it can be easily classified into a well suite category by using K- NN algorithm.
- K-NN algorithm can be used for Regression as well as for Classification but mostly it is used for the Classification problems.
- K-NN is a **non-parametric algorithm**, which means it does not make any assumption on underlying data.
- It is also called a **lazy learner algorithm** because it does not learn from the training set immediately instead it stores the dataset and at the time of classification, it performs an action on the dataset.
- KNN algorithm at the training phase just stores the dataset and when it gets new data, then it classifies that data into a category that is much similar to the new data.

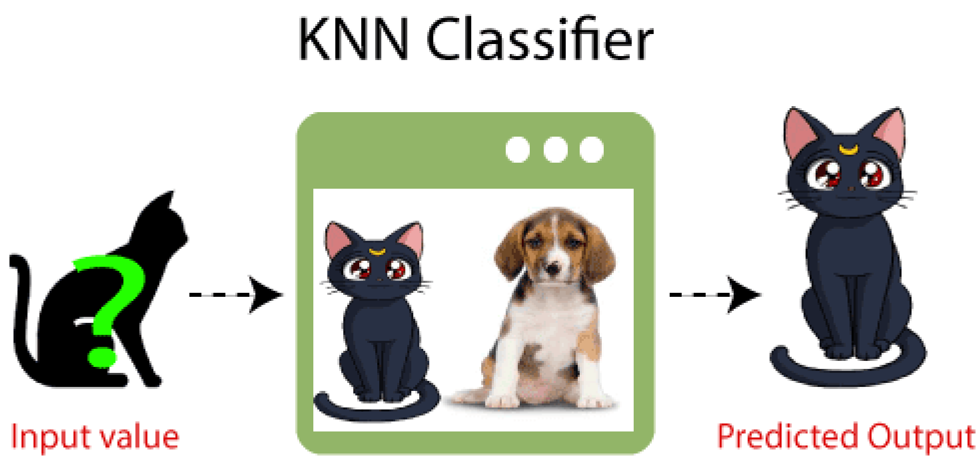


Fig:-8 K-Nearest Neighbour (KNN)

5.6 Support Vector Machine Algorithm:-

Support Vector Machine or SVM is one of the most popular Supervised Learning algorithms, which is used for Classification as well as Regression problems. However, primarily, it is used for Classification problems in Machine Learning.

The goal of the SVM algorithm is to create the best line or decision boundary that can segregate n-dimensional space into classes so that we can easily put the new data point in the correct category in the future. This best decision boundary is called a hyperplane.

SVM chooses the extreme points/vectors that help in creating the hyperplane. These extreme cases are called as support vectors, and hence algorithm is termed as Support Vector Machine. Consider the below diagram in which there are two different categories that are classified using a decision boundary or hyperplane:

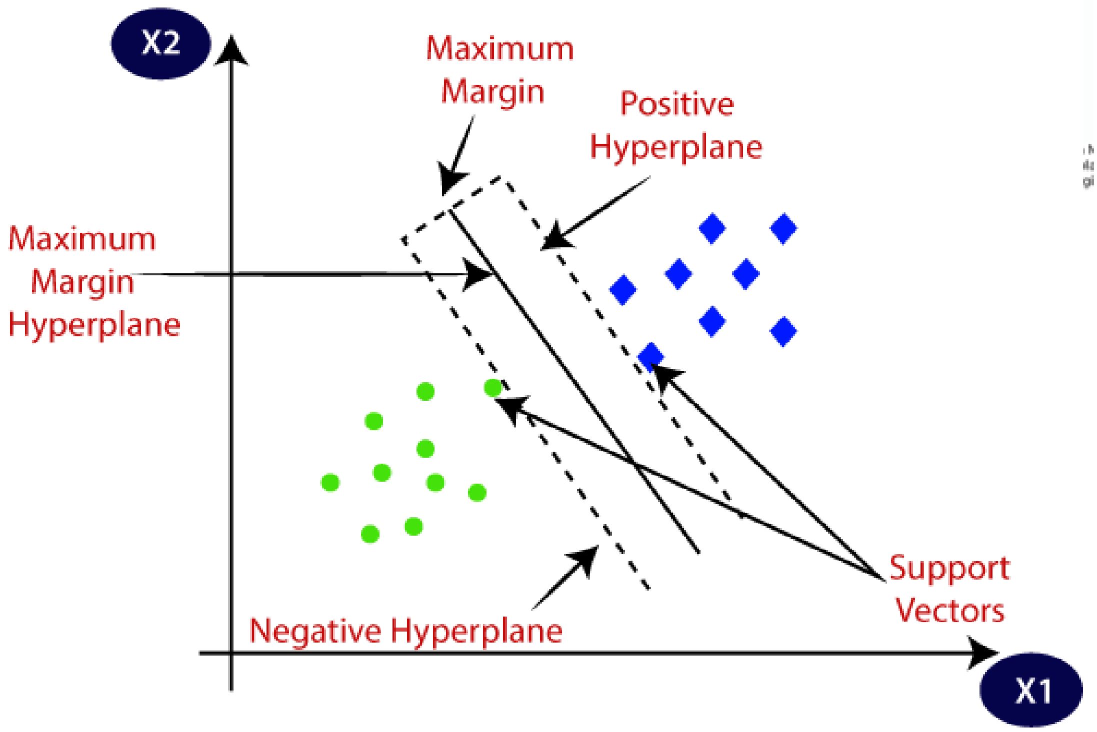


Fig:-9 Support Vector Machine Algorithm

5.7 Random Forest Algorithm:-

Random Forest is a popular machine learning algorithm that belongs to the supervised learning technique. It can be used for both Classification and Regression problems in ML. It is based on the concept of ensemble learning, which is a process *of* combining multiple classifiers to solve a complex problem and to improve the performance of the model.

As the name suggests, "Random Forest is a classifier that contains a number of decision trees on various subsets of the given dataset and takes the average to improve the predictive accuracy of that dataset." Instead of relying on one decision tree, the random forest takes the prediction from each tree and based on the majority votes of predictions, and it predicts the final output.

The greater number of trees in the forest leads to higher accuracy and prevents the problem of overfitting.

The below diagram explains the working of the Random Forest algorithm:

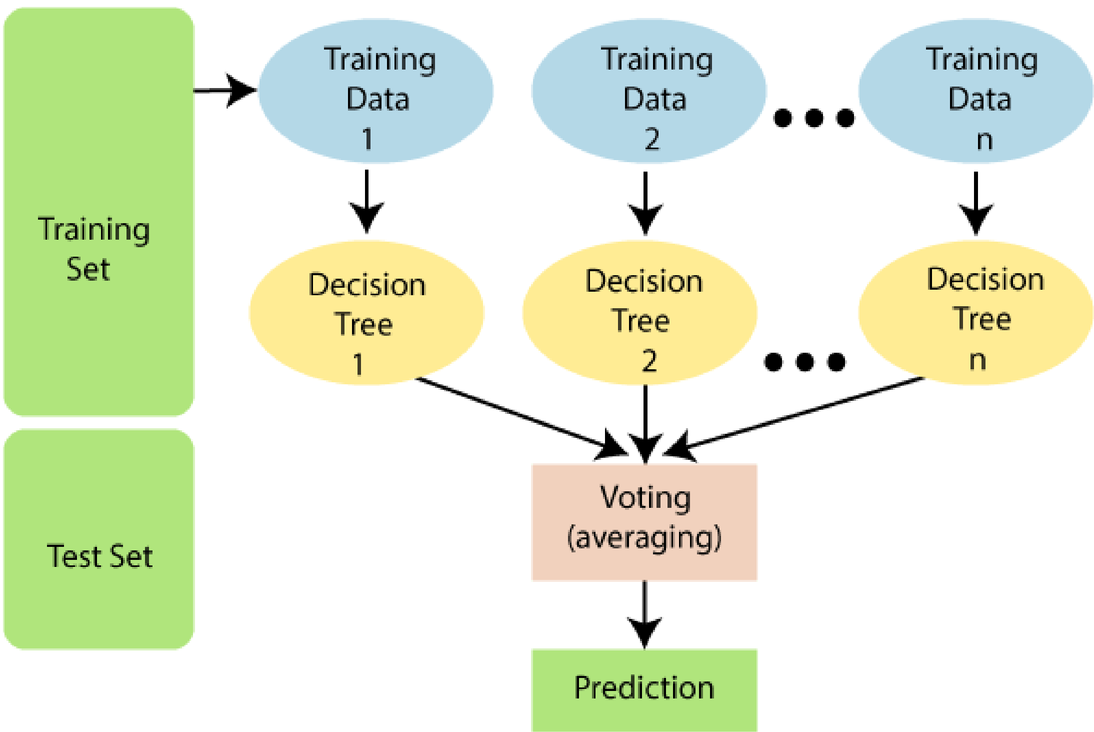


Fig:-10 Random Forest Algorithm

5.8 MLP classification

Multi-Layer perceptron defines the most complex architecture of artificial neural networks. It is substantially formed from multiple layers of the perceptron. TensorFlow is a very popular deep learning framework released by, and this notebook will guide to build a neural network with this library. If we want to understand what is a Multi-layer perceptron, we have to develop a multi-layer perceptron from scratch using Numpy.

The pictorial representation of multi-layer perceptron learning is as shown below-

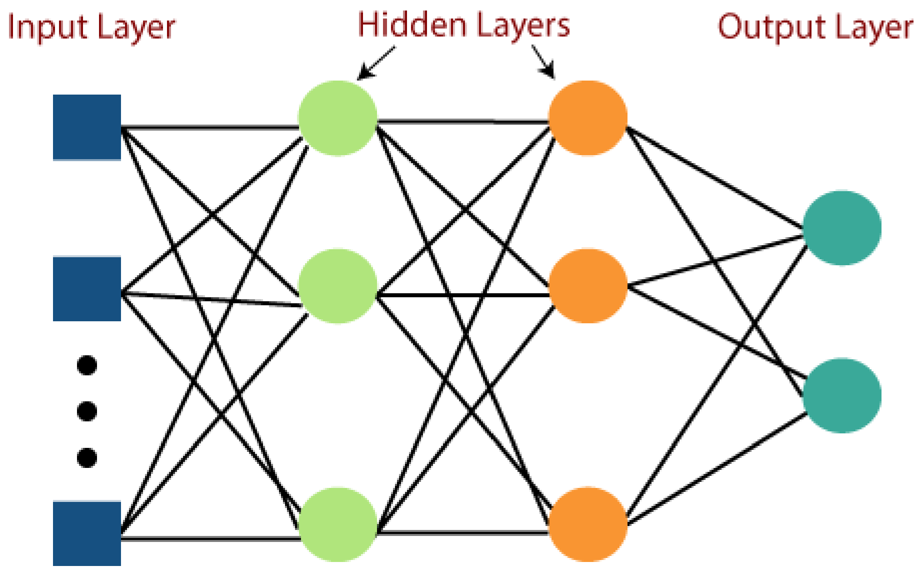


Fig:-11 MLP classification

MLP networks are used for supervised learning format. A typical learning algorithm for MLP networks is also called **back propagation's algorithm**.

A multilayer perceptron (MLP) is a feed forward artificial neural network that generates a set of outputs from a set of inputs. An MLP is characterized by several layers of input nodes connected as a directed graph between the input nodes connected as a directed graph between the input and output layers. MLP uses backpropagation for training the network. MLP is a deep learning method.

6. METHODOLOGY

In this Project, we present the methodology of the proposed age and gender detection system. The first step is to input the data. The second step is tokenization and extraction of the feature sets that we will use later to build the classifier, where tokenization of the data means chopping the text into words. The third step is applying string to word vector, which is very important as it cleans the data by removing unnecessary information in order to improve system performance. The fourth step is applying feature selection to the data. The fifth step is applying the classifier using different algorithms namely (support vector machine (SVM), naïve Bayes, decision tree, logistic, random forest, stacking, and multiclass classifier). The last step is producing the output class and evaluating the performance of the model. The classes that we will use in the experiment are gender (male, female) classes, and the age classes (younger, older) classes is to predict the gender and age of the participant, respectively. Fig. 1 describes the age detection methodology. The first-class A is where the age of the participants is less than or equal to 35 years and the and the second class B is where the participants' age is more than 35 years old.

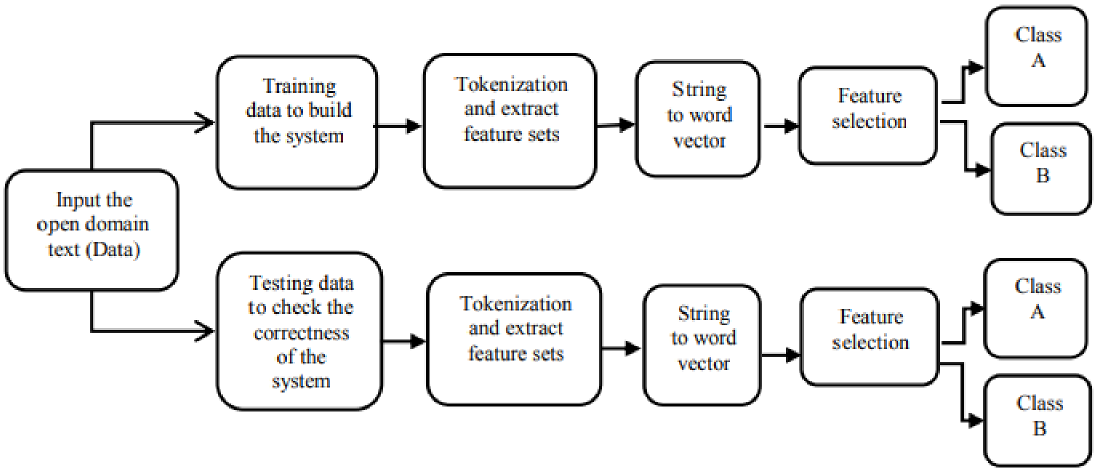


Fig:-12 The proposed age and gender methodology

7. EXPERIMENTAL INVESTIGATIONS

Exploratory Data Analysis

Let's look into the data. We start off by isolating the attributes and look at differences between the genders.

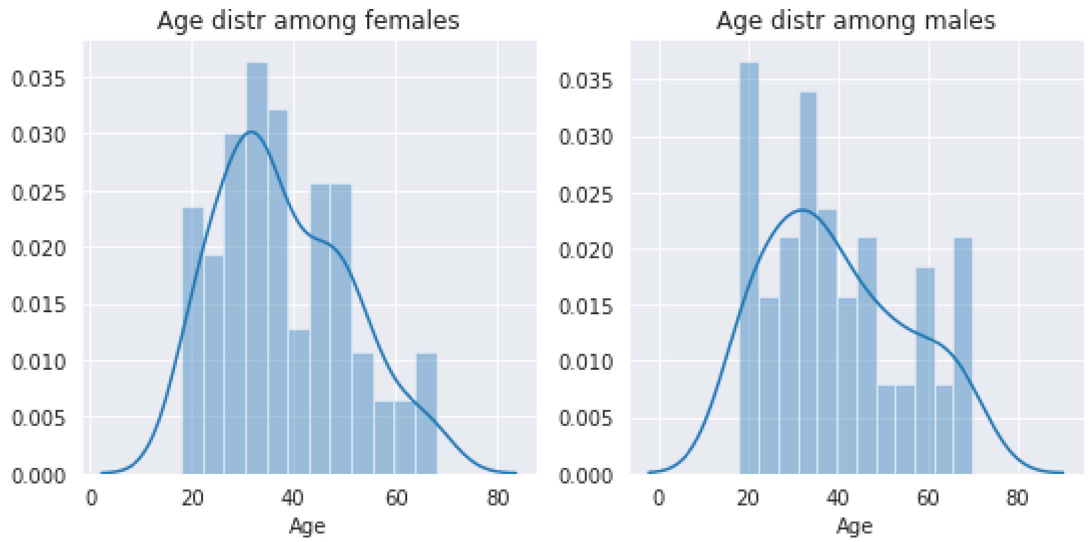


Fig:-13 Age distr among females & males

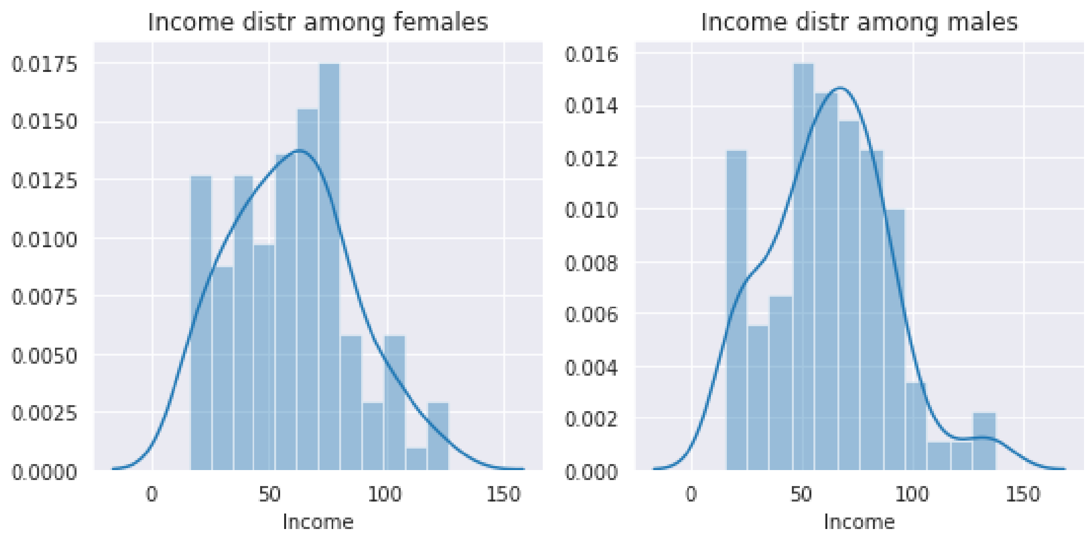


Fig:-14 Income distr among females & males

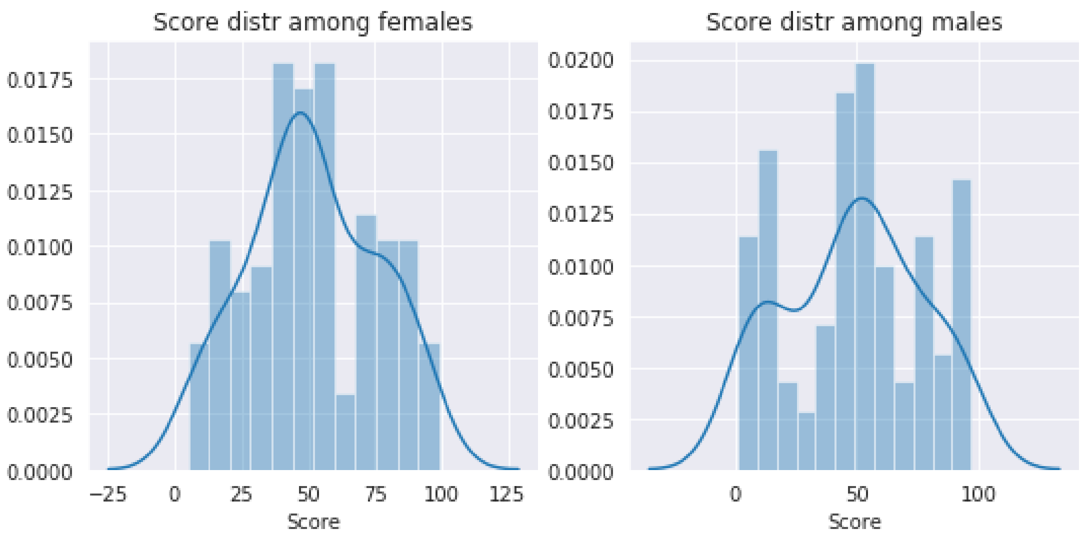


Fig:-15 Score distr among females & males

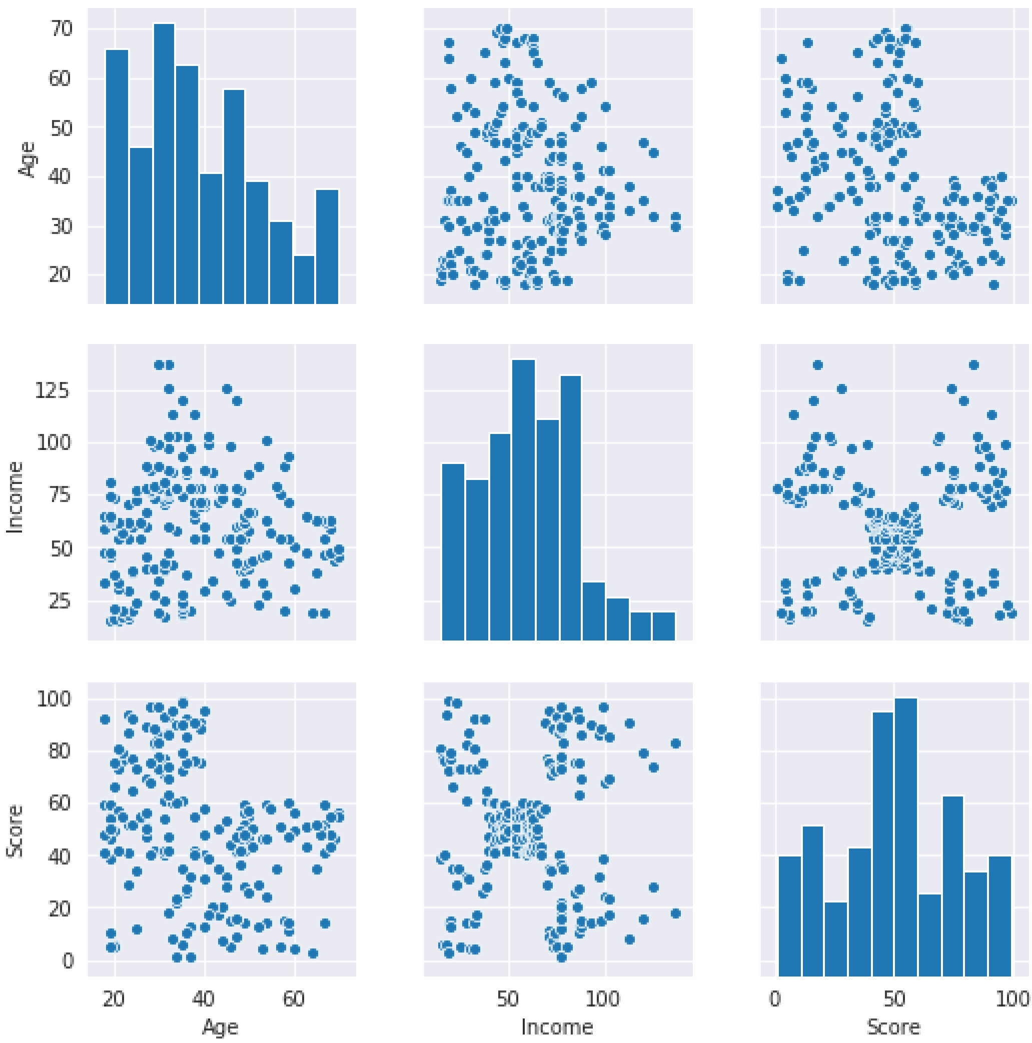


Fig:-16 Comparing pairwise correlations between variables

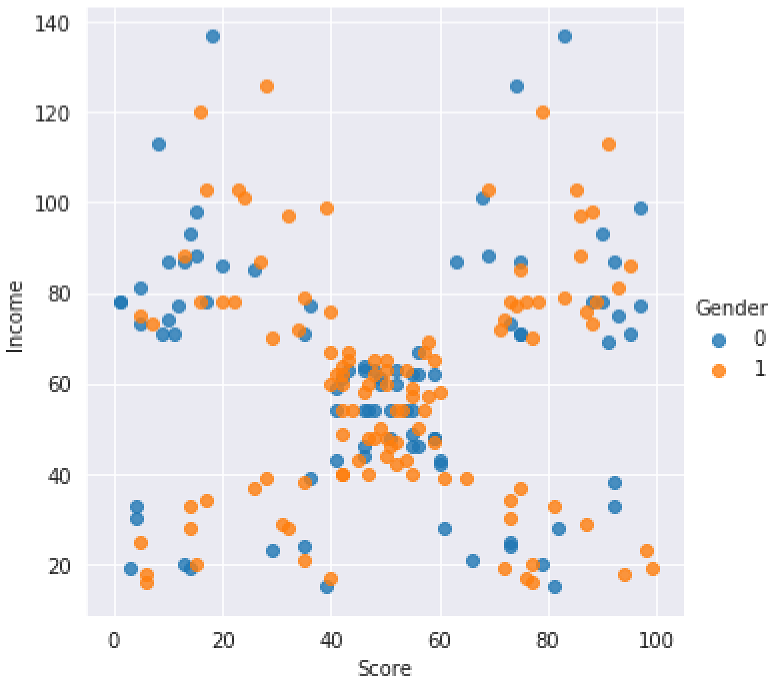


Fig:-17 Income vs Score

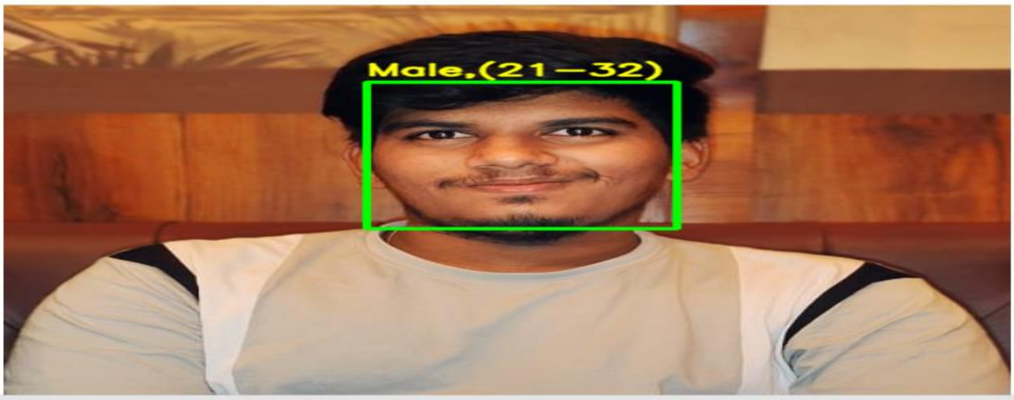
Fig:-18 Error Rate vs K value

8.EXPERIMENTAL RESULTS

➢ Various Algorithm's was Examine to see the Accuracy

8.1 CNN (Convolutional Neural Network)

```
input = cv.imread("/content/Arif project-1.jpeg")
output = age_gender_detector(input)
cv2_imshow(output)
```



8.2 K-Nearest Neighbour (KNN)

```
[24] knn = KNeighborsClassifier(n_neighbors=17)
     knn.fit(X_train, y_train)
     y_pred = knn.predict(X_test)

     print(confusion_matrix(y_test, y_pred))
     print(classification_report(y_test, y_pred))
     print ('Accuracy Score: ' + str(accuracy_score(y_test, y_pred)))
```

```
[[ 7 18]
 [ 3 32]]
              precision    recall  f1-score   support

           0       0.70      0.28      0.40        25
           1       0.64      0.91      0.75        35

    accuracy                           0.65        60
   macro avg       0.67      0.60      0.58        60
weighted avg       0.67      0.65      0.61        60

Accuracy Score: 0.65
```

8.3 Support Vector Machine Algorithm

SVM

```
[29] from sklearn.svm import SVC

     svm = SVC()
     svm.fit(X_train, y_train)
     y_pred = svm.predict(X_test)
```

```
[30] print (confusion_matrix(y_test, y_pred))
     print (classification_report(y_test, y_pred))
     print ('Accuracy Score: ' + str(accuracy_score(y_test, y_pred)))
```

```
[[ 8 17]
 [ 7 28]]
              precision    recall  f1-score   support

           0       0.53      0.32      0.40        25
           1       0.62      0.80      0.70        35

    accuracy                           0.60        60
   macro avg       0.58      0.56      0.55        60
weighted avg       0.59      0.60      0.57        60

Accuracy Score: 0.6
```

8.4 Random Forest Algorithm

Random Forest

```
[25] from sklearn.ensemble import RandomForestClassifier

     forest = RandomForestClassifier(n_estimators=100, random_state=101)
     forest.fit(X_train, y_train)
     y_pred = forest.predict(X_test)
```

```
[26] print (confusion_matrix(y_test, y_pred))
     print (classification_report(y_test, y_pred))
     print ('Accuracy Score: ' + str(accuracy_score(y_test, y_pred)))
```

```
[[ 8 17]
 [12 23]]
              precision    recall  f1-score   support

           0       0.40      0.32      0.36        25
           1       0.57      0.66      0.61        35

    accuracy                           0.52        60
   macro avg       0.49      0.49      0.48        60
weighted avg       0.50      0.52      0.51        60

Accuracy Score: 0.5166666666666667
```

8.5 MLP classification

MLPClassifier

```
from sklearn.neural_network import MLPClassifier

clf = MLPClassifier()
clf.fit(X_train, y_train)
y_pred = clf.predict(X_test)
```

```
/usr/local/lib/python3.7/dist-packages/sklearn/neural_network/_multilayer_perceptron.py
  ConvergenceWarning,
```

```
[34] print (confusion_matrix(y_test, y_pred))
print (classification_report(y_test, y_pred))
print ('Accuracy Score: ' + str(accuracy_score(y_test, y_pred)))
```

```
[[ 7 18]
 [10 25]]
              precision    recall  f1-score   support

           0       0.41      0.28      0.33        25
           1       0.58      0.71      0.64        35

    accuracy                           0.53        60
   macro avg       0.50      0.50      0.49        60
weighted avg       0.51      0.53      0.51        60

Accuracy Score: 0.5333333333333333
```

9.DISCUSSION OF RESULTS

9.1 Conclusion

Neither KNN, Random Forest ,the SVM algorithm nor MLP Classifier are very useful in terms of predicting the gender of the customer based on the features Age, Income and Score. This indicates that the data does not have prediction capability. This doesn't come as a huge surprise, as we could already see in the EDA that there was little that suggested any major differences between the two genders when it came to these variables. However, the sample used is very small (n=200), and having more data might have given us higher accuracy scores.

A high error rate indicates that the model is underfitting and has high bias. The model is not sufficiently complex, so it's simply not capable of representing the relationship between y and the input features. To combat this we could try increasing the number of input features.

CNN can be used to provide improved age and gender classification results, even considering the much smaller size of contemporary unconstrained image sets labeled for age and gender. The simplicity of the model implies that more elaborate systems using more training data may well be capable of substantially improving results beyond these results. One can also try to use a regression model instead of classification for Age Prediction if enough data is available

The goal of this Project was to predict the age and gender of the writers of deceptive text. A complete model was trained and tested with several classifiers on a data set to determine the gender and age the writers of deceptive text. In order to achieve the highest accuracy possible, gain-based feature selection was implemented to removes irrelevant and redundant features that do not have high impact. The experimental results outperform the existing techniques that deal with open domain text. The best results are achieved for gender prediction using features (CFG) with accuracy of 96% via the CNN. On the other hand the best prediction for age was achieved using CFG with accuracy of 96% via the CNN.

Dataset	Algorithm’s	Accuracy
Mall Customers	CNN	96%
Mall Customers	SVM	60%
Mall Customers	Random Forest Classifier	51%
Mall Customers	KNN	65%
Mall Customers	MLPCLASSIFER	53%

Table: - Performance comparison

10.REFERENCES

[1] T. Ahonen, A. Hadid, and M. Pietikainen. Face description with local binary patterns: Application to face recognition.Trans. Pattern Anal. Mach. Intell., 28(12):2037–2041, 2006.

[2] S. Baluja and H. A. Rowley. Boosting sex identification performance. Int. J. Comput. Vision, 71(1):111–119, 2007.

[3] A. Bar-Hillel, T. Hertz, N. Shental, and D. Weinshall. Learning distance functions using equivalence relations. In Int.Conf. Mach. Learning, volume 3, pages 11–18, 2003.

[4] W.-L. Chao, J.-Z. Liu, and J.-J. Ding. Facial age estimation based on label-sensitive learning and age-oriented regression. Pattern Recognition, 46(3):628–641, 2013.

[5] K. Chatfield, K. Simonyan, A. Vedaldi, and A. Zisserman. Return of the devil in the details: Delving deep into convolutional nets. arXiv preprint arXiv:1405.3531, 2014.

[6] J. Chen, S. Shan, C. He, G. Zhao, M. Pietikainen, X. Chen,and W. Gao. Wld: A robust local image descriptor. Trans.Pattern Anal. Mach. Intell., 32(9):1705–1720, 2010.

[7] S. E. Choi, Y. J. Lee, S. J. Lee, K. R. Park, and J. Kim. Ageestimation using a hierarchical classifier based on global and local facial features. Pattern Recognition, 44(6):1262–1281,2011.

[8] T. F. Cootes, G. J. Edwards, and C. J. Taylor. Active appearance models. In European Conf. Comput. Vision, pages 484–498. Springer, 1998.

[9] C. Cortes and V. Vapnik. Support-vector networks. Machine learning, 20(3):273–297, 1995.

[10] E. Eidinger, R. Enbar, and T. Hassner. Age and gender estimation of unfiltered faces. Trans. on Inform. Forensics and

Security, 9(12), 2014. 1, 2, 5, 6

[11] Y. Fu, G. Guo, and T. S. Huang. Age synthesis and estimation via faces: A survey. Trans. Pattern Anal. Mach. Intell., 32(11):1955–1976, 2010.

[12] Y. Fu and T. S. Huang. Human age estimation with regression on discriminative aging manifold. Int. Conf. Multimedia, 10(4):578–584, 2008.

[13] K. Fukunaga. Introduction to statistical pattern recognition.Academic press, 1991.

[14] A. C. Gallagher and T. Chen. Understanding images of groups of people. In Proc. Conf. Comput. Vision Pattern Recognition, pages 256–263. IEEE, 2009.

[15] F. Gao and H. Ai. Face age classification on consumer images with gabor feature and fuzzy lda method. In Advances in biometrics, pages 132–141. Springer, 2009.

[16] X. Geng, Z.-H. Zhou, and K. Smith-Miles. Automatic age estimation based on facial aging patterns. Trans. Pattern Anal. Mach. Intell., 29(12):2234–2240, 2007.

[17] B. A. Golomb, D. T. Lawrence, and T. J. Sejnowski. Sexnet:A neural network identifies sex from human faces. In Neural Inform. Process. Syst., pages 572–579, 1990.

[18] A. Graves, A.-R. Mohamed, and G. Hinton. Speech recognition with deep recurrent neural networks. In Acoustics,Speech and Signal Processing (ICASSP), 2013 IEEE International Conference on, pages 6645–6649. IEEE, 2013.

[19] G. Guo, Y. Fu, C. R. Dyer, and T. S. Huang. Imagebased human age estimation by manifold learning and locally adjusted robust regression. Trans. Image Processing,17(7):1178–1188, 2008.

[20] G. Guo, G. Mu, Y. Fu, C. Dyer, and T. Huang. A study on automatic age estimation using a large database. In Proc. Int.Conf. Comput. Vision, pages 1986–1991. IEEE, 2009.

[21] H. Han, C. Otto, and A. K. Jain. Age estimation from face images: Human vs. machine performance. In Biometrics (ICB), 2013 International Conference on. IEEE, 2013.

[22] T. Hassner. Viewing real-world faces in 3d. In Proc. Int.Conf. Comput. Vision, pages 3607–3614. IEEE, 2013.

[23] T. Hassner, S. Harel, E. Paz, and R. Enbar. Effective face frontalization in unconstrained images. Proc. Conf. Comput.Vision Pattern Recognition, 2015.

[24] G. E. Hinton, N. Srivastava, A. Krizhevsky, I. Sutskever, and R. R. Salakhutdinov. Improving neural networks by preventing co-adaptation of feature detectors. arXiv preprintarXiv:1207.0580, 2012.

[25] G. B. Huang, M. Ramesh, T. Berg, and E. Learned-Miller.Labeled faces in the wild: A database for studying face recognition in unconstrained environments. Technical report, Technical Report 07-49, University of Massachusetts,Amherst, 2007.

[26] Y. Jia, E. Shelhamer, J. Donahue, S. Karayev, J. Long, R. Girshick, S. Guadarrama, and T. Darrell. Caffe: Convolutional architecture for fast feature embedding. arXiv preprintarXiv:1408.5093, 2014.

[27] A. Karpathy, G. Toderici, S. Shetty, T. Leung, R. Sukthankar, and L. Fei-Fei. Large-scale video classification with convolutional neural networks. In Proc. Conf. Comput. VisionPattern Recognition, pages 1725–1732. IEEE, 2014.

[28] A. Krizhevsky, I. Sutskever, and G. E. Hinton. Imagenet classification with deep convolutional neural networks. In Neural Inform. Process. Syst., pages 1097–1105, 2012.

[29] Y. H. Kwon and N. da Vitoria Lobo. Age classification from facial images. In Proc. Conf. Comput. Vision Pattern Recognition, pages 762–767. IEEE, 1994.

[30] A. Lanitis. The FG-NET aging database, 2002. Available: www-prima.inrialpes.fr/FGnet/html/

benchmarks.html.

[31] Y. LeCun, B. Boser, J. S. Denker, D. Henderson, R. E.Howard, W. Hubbard, and L. D. Jackel. Backpropagation applied to handwritten zip code recognition. Neural computation, 1(4):541–551, 1989.

[32] C. Liu and H. Wechsler. Gabor feature based classification using the enhanced fisher linear discriminant model for facerecognition. Trans. Image Processing, 11(4):467–476, 2002.

[33] P. Luo, X. Wang, and X. Tang. Hierarchical face parsing via deep learning. In Proc. Conf. Comput. Vision Pattern Recognition, pages 2480–2487. IEEE, 2012.

[34] E. Makinen and R. Raisamo. Evaluation of gender classification methods with automatically detected and aligned faces.Trans. Pattern Anal. Mach. Intell., 30(3):541–547, 2008.

[35] B. Moghaddam and M.-H. Yang. Learning gender with support faces. Trans. Pattern Anal. Mach. Intell., 24(5):707–711, 2002.

[36] X. Niyogi. Locality preserving projections. In Neural Inform. Process. Syst., volume 16, page 153. MIT, 2004.

[37] A. J. O’toole, T. Vetter, N. F. Troje, H. H. Bulthoff, et al. Sex ¨classification is better with three-dimensional head structurethan with image intensity information. Perception, 26:75–84,1997.

[38] C. Perez, J. Tapia, P. Estevez, and C. Held. Gender classification from face images using mutual information and feature fusion. International Journal of Optomechatronics, 6(1):92–119, 2012.

[39] P. J. Phillips, H. Wechsler, J. Huang, and P. J. Rauss. The feret database and evaluation procedure for face-recognition algorithms. Image and vision computing, 16(5):295–306,1998.

[40] L. Rabiner and B.-H. Juang. An introduction to hidden markov models. ASSP Magazine, IEEE, 3(1):4–16, 1986.

[41] N. Ramanathan and R. Chellappa. Modeling age progression in young faces. In Proc. Conf. Comput. Vision Pattern Recognition, volume 1, pages 387–394. IEEE, 2006.

[42] D. Reid, S. Samangooei, C. Chen, M. Nixon, and A. Ross.Soft biometrics for surveillance: an overview. Machine learning: theory and applications. Elsevier, pages 327–352,2013.

[43] K. Ricanek and T. Tesafaye. Morph: A longitudinal image database of normal adult age-progression. In Int. Conf. on Automatic Face and Gesture Recognition, pages 341–345.IEEE, 2006.

[44] M. Riesenhuber and T. Poggio. Hierarchical models of object recognition in cortex. Nature neuroscience, 2(11):1019–1025, 1999.

[45] O. Russakovsky, J. Deng, H. Su, J. Krause, S. Satheesh,S. Ma, Z. Huang, A. Karpathy, A. Khosla, M. Bernstein,A. C. Berg, and L. Fei-Fei. ImageNet Large Scale VisualRecognition Challenge, 2014.

[46] C. Shan. Learning local binary patterns for gender classification on real-world face images. Pattern Recognition Letters,33(4):431–437, 2012.

[47] Y. Sun, X. Wang, and X. Tang. Deep convolutional network cascade for facial point detection. In Proc. Conf. Comput.Vision Pattern Recognition, pages 3476–3483. IEEE, 2013.

[48] Y. Sun, X. Wang, and X. Tang. Deep learning face representation from predicting 10,000 classes. In Proc. Conf. Comput. Vision Pattern Recognition, pages 1891–1898. IEEE,2014.

[49] M. Toews and T. Arbel. Detection, localization, and sex classification of faces from arbitrary viewpoints and under occlusion. Trans. Pattern Anal. Mach. Intell., 31(9):1567–1581,2009.

[50] A. Toshev and C. Szegedy. Deeppose: Human pose estimation via deep neural networks. In Proc. Conf. Comput. Vision Pattern Recognition, pages 1653–1660. IEEE, 2014.

[51] I. Ullah, M. Hussain, G. Muhammad, H. Aboalsamh, G. Bebis, and A. M. Mirza. Gender recognition from face images with local wld descriptor. In Systems, Signals and ImageProcessing, pages 417–420. IEEE, 2012.

[52] V. N. Vapnik and V. Vapnik. Statistical learning theory, volume 1. Wiley New York, 1998.

[53] L. Wolf, T. Hassner, and Y. Taigman. Descriptor based methods in the wild. In post-ECCV Faces in Real-Life ImagesWorkshop, 2008.

[54] S. Yan, M. Liu, and T. S. Huang. Extracting age information from local spatially flexible patches. In Acoustics, Speech and Signal Processing, pages 737–740. IEEE, 2008.

[55] S. Yan, X. Zhou, M. Liu, M. Hasegawa-Johnson, and T. S.Huang. Regression from patch-kernel. In Proc. Conf. Comput. Vision Pattern Recognition. IEEE, 2008.

[56] X. Zhuang, X. Zhou, M. Hasegawa-Johnson, and T. Huang.Face age estimation using patch-based hidden markov model supervectors. In Int. Conf. Pattern Recognition. IEEE, 2008.

<u>Acceptance Letter</u>

To
Dr./Mr./Ms.
Sahiti Vankayalapati, Lakshman Pappula, Ktps Kumar, Nikhil Vishnu Batchu, Arif Dalali Narendra Datta Inti and Nageshwara Rao Netinti

Paper ID: **ICACCS_2022_paper_496**

Dear Sir/Madam,

Sub: Acceptance Letter – IEEE 2022 8th International Conference on Advanced Computing and Communication Systems (ICACCS). 25th – 26th March 2022 Technically Sponsored by IEEE and IEEE Madras Section.

The organizing Committee is pleased to inform you that the peer- reviewed and refereed conference paper titled as "**Application of Binary Particle Swarm Optimization Algorithm for Thinned Planar Antenna Array Synthesis**", has been conditionally accepted for Hybrid (Oral/Virtual) presentation at the ICACCS 2022 conference on 25th – 26th March 2022.

We would like to kindly invite you to register for the conference on or before 18.03.2022 and present the paper at the conference venue in Coimbatore. On behalf of the organizing committee, I would like to congratulate you.

Note: Authors can present their paper through virtual / video conferencing.

Dr. H. Anandakumar
Conference Chair – ICACCS 2022

Sri Eshwar College of Engineering (Autonomous), Coimbatore, Tamil Nadu, India

Submission Information

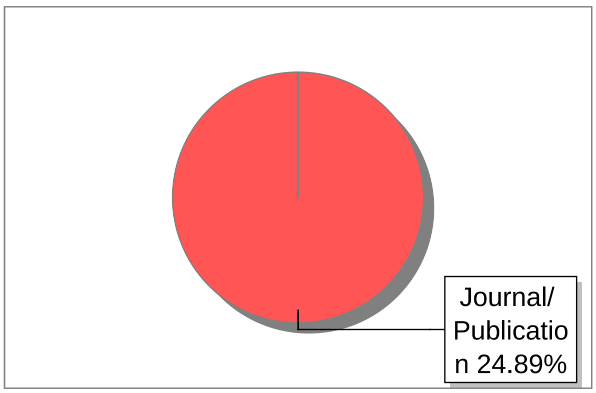
Author Name	18IEDCMP11
Title	project
Paper/Submission ID	475547
Submission Date	2022-03-17 19:30:43
Total Pages	33
Document type	Research Paper

Result Information

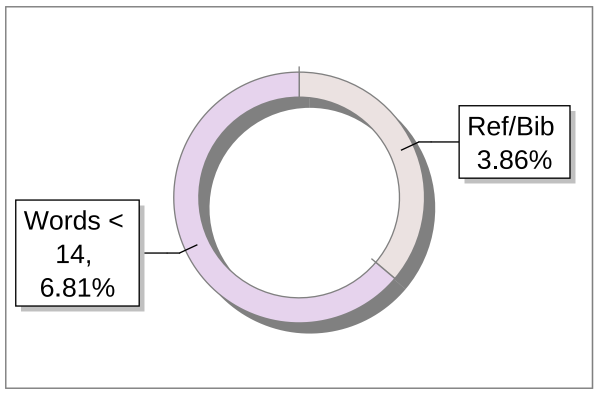
Similarity **25 %**

1 10 20 30 40 50 60 70 80 90

Sources Type



Report Content



Exclude Information

Quotes	Not Excluded
References/Bibliography	Excluded
Sources: Less than 14 Words Similarity	Not Excluded
Excluded Source	**0 %**
Excluded Phrases	Not Excluded

A Unique QR Code use to View/Download/Share Pdf File

DrillBit

DrillBit Similarity Report

25	26	B	A-Satisfactory (0-10%) B-Upgrade (11-40%) C-Poor (41-60%) D-Unacceptable (61-100%)
SIMILARITY %	MATCHED SOURCES	GRADE	

LOCATION	MATCHED DOMAIN	%	SOURCE TYPE
1	talhassner.github.io	10	Publication
2	Suspected necrolytic migratory ervthema associated with chronic hepatopathy in a by D-2000	5	Publication
3	A Comparison of Loss Weighting Strategies for Multi task Learning in Deep Neural by Gong-2019	1	Publication
4	www.ijmlc.org	1	Publication
5	IEEE 2019 1st International Conference on Advances in Science, Engin	1	Publication
6	Plasma production of nanodevice-grade semiconductor nanocrystals by Holman-2011	1	Publication
7	Kindergarten oral language skill A key variable in the intergenerational transm by Rache-2007	<1	Publication
8	Wavelet Domain Multifractal Analysis for Static and Dynamic Texture Cl by Hu-2013	<1	Publication
9	Real-Time Vision Based Driver Drowsiness Detection Using Partial Least Squares A by Selvakumar-2015	<1	Publication
10	cs231n.stanford.edu	<1	Publication
11	Convolutional neural networks (CNN) for feature-based model calibration under un by Moh-2020	<1	Publication

12	An Intelligent Anti-Jamming Scheme for Cognitive Radio Based on Deep Reinforceme by Xu-2020	<1	Publication
13	Stacked autoencoder based weak supervision for social image understan, by Xu, Chaoyang Dai, - 2019	<1	Publication
14	Schur Indices and Schur Groups, II by Ud-1996	<1	Publication
15	www.dx.doi.org	<1	Publication
16	www.dx.doi.org	<1	Publication
17	www.dx.doi.org	<1	Publication
18	www.doaj.org	<1	Publication
19	The formation times and building blocks of Milky Way-mass galaxies in the FIRE s by Santistevan-2020	<1	Publication
20	Partially shaded sketch-based image search in real mobile device envir by Ahmad-2018	<1	Publication
21	Lessons in character education incorporating neoliberal learning in classroom r by Jerome-2020	<1	Publication
22	Legal Issues Patenting Price Gouging by Pike-2015	<1	Publication
23	International control of tritium to prevent horizontal proliferation and to fost by Kalinowski-1995	<1	Publication
24	Deep hashing network for material defect image classification, by Yang, Kai Sun, Zhi- 2018	<1	Publication
25	An increase of intelligence in Saudi Arabia, 19772010 by Batterjee-2013	<1	Publication
26	IEEE 2013 IEEE 13th International Conference on Data Mining Workshop by	<1	Publication

Koneru Lakshmaiah Education Foundation

(Deemed to be University estd., u/s 3 of UGC Act 1956)

Greenfields, Vaddeswaram, Guntur (Dist.), Andhra Pradesh - 522502

APRIL, 2022