# VEHICLE USER AUTHENTICATION USING OPENCY

A Major Project Report Submitted in Partial fulfillment for the award of Bachelor of Technology in Computer Science & Engineering

## Submitted to RAJIV GANDHI PROUDYOGIKI VISHWAVIDYALAYA BHOPAL (M.P)



#### MAJOR PROJECT REPORT

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#### LAKSHMI NARAIN COLLEGE OF TECHNOLOGY, BHOPAL

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#### **CERTIFICATE**

This is to certify that the work embodied in this project work entitled "Vehicle User Authentication using OpenCV" has been satisfactorily completed by the Abhishek Jain (0103CS171006), Bhola Prasad Chilhate (0103CS171046), Krishna Yadav (0103CS171072) and Ojasva Saxena (0103CS171091). It is a bonafide piece of work, carried out under the guidance in Department of Computer Science & Engineering, Lakshmi Narain College of Technology, Bhopal for the partial fulfillment of the Bachelor of Technology during the academic year 2020-2021.

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We would also thank our institution and all the faculty members without whom this project work would have been a distant reality.

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#### INTRODUCTION

Many countries require drivers to hold a license to legally operate a motor vehicle and reserve the right to suspend or disqualify this license if road rules are not obeyed. Despite such laws, several people drive unlicensed, either having never obtained a license or continuing to drive after their license has been suspended or disqualified (Griffin & DeLaZerda, 2000; Knox et al., 2003). These unlicensed drivers are thought to be at higher risk of motor vehicle injury than their licensed counterparts, but this has been difficult to prove (Federal Office of road Safety, 1997a; Griffin & DeLaZerda, 2000; Knox et al., 2003). Several studies of unlicensed drivers have suggested that they are more likely to engage in risky driving behaviors such as speeding, drink driving, red light running, and non-use of seatbelts, than those with a valid license (Federal Office of Road Safety, 1997; Retting et al., 1999; Griffin & DeLaZerda 2000; Kim & Kim, 2003).

It has also been suggested that unlicensed drivers may be over-represented in crash statistics (Federal Office of Road Safety, 1997; Griffin & DeLaZerda, 2000), but this has not been conclusively demonstrated because of a lack of comparative data on the prevalence of unlicensed driving in the general driving population (DeYoung et al., 1997; Knox, 2003). Studies of crashed drivers have found that compared to licensed drivers, unlicensed drivers are more likely to be at fault (Perneger & Smith, 1991; Land Transport Safety Authority, 2003) and more seriously injured (Harrison, 1997) when involved in a crash. These studies used control drivers who were involved in a crash, rather than population-based controls, so were unable to determine the excess risk of car crash injury for unlicensed drivers. Only one previous study has estimated the driving exposure of suspended/revoked and unlicensed drivers, using a "quasi-induced" exposure estimation method (DeYoung et al., 1997). This study found that both groups were at higher risk of crash involvement compared to validly licensed drivers, but caution that their exposure estimates are likely to be subject to significant bias.

There remains a lack of estimates of the prevalence of unlicensed driving amongst the general driving population, and because of this the excess risk of an unlicensed driver's involvement in a crash that leads to injury has not previously been quantified. In New Zealand,

a driver's license is obtained by completing a series of applications and driving tests, and payment of several fees. Unlicensed drivers may have not undertaken this licensing process, or they may have had their license suspended or disqualified for a variable period of time as a result of offences such as drink driving, speeding, or other serious infringements of the road rules (Land Transport Safety Authority, 2004). We used data from a population-based case-control study conducted in the Auckland region of New Zealand to examine the prevalence of unlicensed driving in the regional driving population, and the relationship between unlicensed driving and car crash injury.

Previous studies have indicated that unlicensed drivers are more likely to engage in risky driving behaviors and are more likely than licensed drivers to be at fault and more seriously injured when involved in a crash. However, the prevalence of unlicensed drivers in the general driving population has not been measured, and the risk of an unlicensed driver being involved in an injury crash has not been quantified. We examined the association between unlicensed driving and car crash injury using data from a population-based case control study Methods.

A study Stats population of the drivers of all cars on public roads in the major city region. Cases were 571 vehicles involved in a crash resulting in any occupant being hospitalized or killed, from the study base, during the recruitment period. Controls were 588 vehicles selected from the driving population using a random cluster sampling method. The drivers of all vehicles completed a structured interview covering multiple potentially crash-related factors.

Driving unlicensed was reported by 12% of case and 1% of control drivers. Unlicensed drivers were at significantly higher risk of car crash injury than those holding a valid license (odds ratio 11.1, 95% confidence interval 4.2 to 29.7) after adjustment for age and sex. After further adjustment for education level, ethnicity, driving exposure, time of day, sleepiness score, year of vehicle manufacture, passenger carriage, seatbelt use, blood alcohol concentration, and travelling speed at time of crash, the increased risk was still present but no longer significant (OR 3.9, 95% CI 0.7–22.4). Conclusions. Unlicensed drivers are a high-risk group for car crash injury after taking other crash-related risk factors into account. Strategies to reduce unlicensed driving may therefore facilitate reductions in road crashes, although further work is needed in this area.

This research project uses the help of new modern breakthroughs in AI and ML to implement better solution to authenticate a user before riding a vehicle. This project aims at developing a solution to authenticate or verify a user before using a vehicle.

The system would ask for user's driver's license to get details about the person, then it would also take video feed from the camera installed in front of driver's seat to verify the person, and finally decide whether to give access to the vehicle's controls or not. The driver and his original driver's license are a must for this authentication system.

The working of the system would be displayed by developing an interactive and simplistic website, which would be using general directory system for storing user's data temporarily. This website would be using OpenCV library for making rapid ML model to verify the identity of a user. This project would be designed by using languages such as Python, HTML, CSS and JavaScript.

#### 2.1 Road accident survey

#### 2.1.1 Introduction

A complete description of the methodology of the study has been published previously (Connor et al., 2002). Recruitment took place from 1998 to 1999 in the major city region, which contains the largest city in New Zealand and a mixture of other urban, suburban, and rural areas. The regional population is about 1.1 million people (Statistics New Zealand, 2001). The study base was defined as all light vehicles driving on non-local public roads in the region. Case vehicles were identified when any occupant of a vehicle from the study base was hospitalized or killed in a crash during the recruitment period. Case identification took place through surveillance at the four hospitals serving the major city region, and through the major city Coroner.

During the study period 615 eligible case drivers were identified and interviews were completed for 571 (93%) of these. Control selection aimed to achieve a representative sample of all driving time for the study base during the recruitment period. Control vehicles were identified during the same time interval and at approximately the same rate as cases. To select controls, a list of roads in the major city region was obtained and 69 roadside sites were randomly selected from this list. A day of the week, time of day, and direction of travel were randomly assigned to each site. Study staff then visited the site at the selected time and vehicles that passed the site during a defined period were randomly selected as control vehicles. The number of vehicles selected from each site was proportional to the volume of traffic at the site. These vehicles were stopped at the roadside and a suitable time for a telephone interview was arranged. During these roadside surveys 746 control cars were identified, and of these, interviews were completed with 588 drivers (79% response rate). Interviews for the drivers of case and control vehicles were conducted by telephone for 204 (36%) case drivers and 576 (98%) control drivers; the remaining interviews were conducted in person. Proxy respondents were interviewed for 57 case drivers and two control drivers who were fatally injured or unable to be interviewed for other reasons. All interviews were based on a structured questionnaire

that included characteristics of the driver, circumstances of the crash, and vehicle characteristics. For control drivers, the interview was referenced to the time of being sampled in the roadside survey.

License status was determined by asking drivers what type of car license they held at the time of the crash or survey. For these analyses, "unlicensed" drivers were those that had never held a car license or whose license was disqualified or suspended at the time of the crash/survey; other types of licenses, including full licenses, learner licenses, and overseas licenses, were considered valid. Blood alcohol level was determined using a breathalyzer for controls and from hospital and police records for cases. Missing data for blood alcohol level was imputed according to self-reported alcohol consumption prior to the crash and the suspicions of ambulance and hospital staff. Details of alcohol imputation have been previously published (Connor et al., 2004). Environmental surveys of crash and control recruitment sites were conducted to measure environmental factors potentially related to crashes. Odds ratios (OR's) and 95% confidence intervals (CIs) were calculated from linear logistic regression models using SUDAAN software, which accounts for intra-cluster correlation of control data sampled from the same site (Shah et al., 1997). For the multivariable analyses, we identified potential confounders from the epidemiological literature and adjusted for these if they were significantly associated with car crash injury in our data after controlling for driver's age and sex. Because unlicensed driving may influence crash risk indirectly through its associations with other risky driving, we examined the association between unlicensed driving and car crash injury by first adjusting only for age and sex. We then adjusted for ethnicity, education level, and driving exposure (average hours spent driving per week), plus acute driving-related exposures at the time of the crash/survey (passenger carriage, time of day, Stanford sleepiness score, year of vehicle manufacture, blood alcohol concentration, seatbelt use, and travelling speed).

We also examined the contribution that each of these confounders made to the age and sex adjusted odds ratio for the association between unlicensed driving and car crash injury. This was done by adding each variable to this model individually and estimating the percentage by which this changed the odds ratio, using the formula 100 ([ORU-ORA]/[ORU – 1])% where ORU and ORA are, respectively, the odds ratios for unlicensed driving and car crash injury unadjusted (except by age and sex) and after further adjustment for each risk factor alone.

#### 2.1.2 Findings

This population-based case control study allowed us to examine the prevalence of unlicensed driving the Auckland regional driving population and the excess risk of car crash injury for unlicensed drivers. Driving unlicensed was reported by 12% of cases in this study, of whom 10% had never held a license and 2% held a license that was currently suspended or disqualified. Unlicensed drivers had about 11 times higher risk of being involved in a serious injury crash compared to drivers holding a valid license after adjustment for age and sex. This positive association was still present after adjusting for other crash-related factors, although it was no longer significant probably due to lack of power.

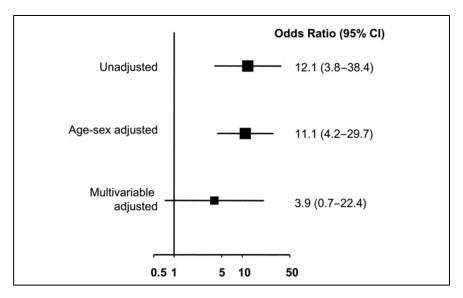


Fig 2.1 Unadjusted, age and sex adjusted, and multivariable adjusted odds ratios

Fig 2.1 shows the unadjusted, age and sex adjusted, and multivariable adjusted odds ratios (95% confidence intervals) for the association between unlicensed driving and car crash injury, Auckland Car Crash Injury Study. The multivariable odds ratio is adjusted for age, sex, ethnicity, education, driving exposure, passenger carriage, time of day, sleepiness score, year of car manufacture, blood alcohol concentration, seatbelt use, and traveling speed at the time of crash.

Our prevalence estimates are consistent with several previous studies. Crash statistics from New Zealand indicate that in 1998, 11% of fatal crashes involved a disqualified or unlicensed driver (Land Transport Safety Authority, 2000). Griffin and DeLaZerda (2000) examined 278,078 drivers involved in fatal crashes using the Fatal Accident Reporting System in the United States. Of these drivers, 11% of these held an invalid license or had no known

license. Harrison (1997) found that of fatal crashes in Victoria, Australia, 2% had a disqualified license. However, there are few previous estimates of the frequency of unlicensed driving amongst the general driving population. In the control population of our study, conceptually representing the Auckland regional driving population, 1% reported being unlicensed or disqualified/suspended at the time of the roadside survey. Using a "quasi-induced" exposure method, also using data from the Fatal Accident Reporting System, DeYoung et al. (1997) estimated that 9% of the driving population in California had a suspended or revoked license. This is higher than our estimate, but the authors of this study note several serious limitations of their estimation methods. Further representative surveys are required to measure the prevalence of unlicensed driving more accurately. We also found a strong association between unlicensed driving and car crash injury after adjustment for age and sex. Even after adjustment for other crash-related risk factors, the point estimate for the odds ratio was about four, although this was no longer significant. This lack of significance is likely to be due to small numbers producing wide confidence intervals.

Our finding that unlicensed drivers are a high-risk driving population is consistent with previous research. Two studies have examined the effect of driving unlicensed on crash severity. Shibata & Fukuda (1994) used data from police-reported traffic crashes of both cars and motorcycles in Fukuoka Prefecture, Japan, comparing characteristics of crash-involved drivers who died to those who were uninjured (Shibata & Fukuda, 1994). After adjustment for age, unlicensed drivers of cars were three times more likely, and drivers of motorcycles nine times more likely, to be killed when involved in a car crash compared to licensed drivers. The association was significant only for motorcycle drivers. Harrison (1997) conducted a similar study of crash-involved drivers in Victoria, Australia, and found a significant difference between the frequency of disqualified licenses amongst fatally injured drivers (4.6%) compared to uninjured drivers (0.7%) in unadjusted analyses (Harrison, 1997). Another study examined the effect of various driver characteristics, including license status, on involvement in an atfault crash (Premerger & Smith, 1991).

Using paired crash data from the Fatal Accident Reporting System in the United States, this study found that drivers with an invalid license were about twice as likely to have initiated the crash compared to those holding a valid license. Our results confirm unlicensed drivers to be a population at high risk of serious car crashes and suggest that unlicensed drivers have three times excess risk of involvement in an injury crash compared to licensed drivers.

Driving unlicensed is unlikely to directly increase the risk of car crash injury and the mechanism by which this population is at risk is probably through associations with other crash-related factors. Of the acute risky driving behaviors, we examined, sleepiness and blood alcohol level accounted for the largest proportion of the age and sex adjusted odds ratio. Other studies have also found evidence that unlicensed drivers may be more likely to display risky driving behaviors, including speeding, drink driving, red-light running, and non-use of seatbelts (Federal Office of Road Safety, 1997b; Retting et al., 1999; Griffin & DeLaZerda, 2000; Kim & Kim, 2003). In our data, education level, ethnicity, and driving exposure were also important contributors to the relationship between unlicensed driving and car crash injury. There were significant associations between unlicensed driving and ethnicity (p = 0.01), with more Maori and Pacific Islanders being both never licensed and holding a disqualified or suspended license.

There were no significant associations between license status and other demographic variables, including age (p = 0.2). Because of small numbers we were not able to fully investigate the relationships between license status and other associated variables; this will be an interesting area for future research. However, although a variety of crash-related variables may account for the relationship between unlicensed driving and car crash injury, explicit knowledge of these need not be a prerequisite for the implementation of countermeasures aimed at unlicensed drivers. Our study has several potential limitations. License status and many of the other variables were self-reported. Because driving unlicensed is illegal in New Zealand, this may be underreported and is therefore a potential source of measurement bias. However, questions on illegal behaviors were embedded in a large questionnaire containing multiple items relating to driving; interviewers were highly trained and assured participants of complete confidentiality. Our data on excess alcohol consumption prior to driving (also illegal in New Zealand) suggest that self-report is a valid measure, as the correlation between selfreported and objective measures of alcohol consumption was high (Spearman correlation coefficient = 0.77). The differential response rate between cases and controls may have introduced selection bias, particularly if non-responders amongst the control population tended to be unlicensed. If this is the case, we are likely to have underestimated the prevalence of unlicensed driving in controls, which would result in an overestimate of the risk of injury crashes. Confounding variables, particularly those that relate to risky and illegal driving, may have also been inaccurately measured.

Case control studies using self-reported data may also be subject to recall bias (Woodward, 2005), although it is difficult to predict what effect this would have on our estimate of effect. The increased risk of injury to vehicle occupants when the driver is unlicensed supports the need for interventions aimed at this population. Other authors have suggested a variety of measures that may be effective, including increasing police resources to enable enforcement, reviewing and broadening the penalties applied, and increasing public awareness of the dangers of unlicensed driving and the penalties involved (Knox et al., 2003). Others have proposed applying barriers to driving including vehicle impoundment, electronic driver licenses, and ignition interlocks when licenses are suspended or disqualified (Griffin & DeLaZerda, 2000). For most jurisdictions, interventions in the short term are likely to focus on enforcement and education strategies. Unlicensed driving is unlikely to be a randomly distributed characteristic and the identification of high-risk groups and risk factors for unlicensed driving, for example, age, gender, ethnicity, socioeconomic status, or lifestyle factors such as hazardous alcohol use, would aid in targeting health promotion strategies. There may also be value in reviewing the suitability of current licensing processes and driver training for these specific groups. Although the primary aim of such interventions should be to reduce unlicensed driving, a harm minimization approach aiming to decrease risky driving amongst unlicensed drivers may also achieve a reduction in injuries.

The mean age of case drivers was 36.6 years, and control drivers 40.8 years. The case group was 65% male and the control group were 59% male. There were no significant differences in age group, sex, or driving conditions, between drivers who were interviewed and all eligible drivers, for both case and control vehicles.

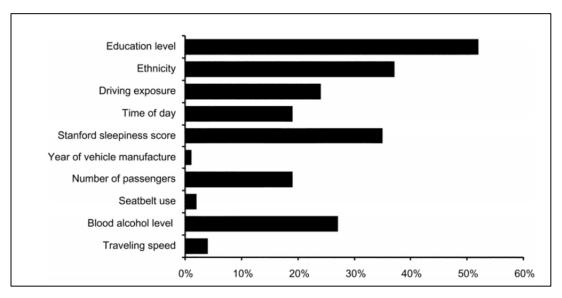


Fig 2.2 Proportion of the age and sex adjusted odds ratio for unlicensed driving and car crash injury explained by other risk factors, Auckland Car Crash Injury Study.

The prevalence of unlicensed driving at the time of the crash/survey was 11.6% (n = 66) amongst cases and 1.1% (n = 7) amongst controls. Missing data for both cases and controls was less than 1% for license status, and less than 10% for all variables used in these analyses after imputation for blood alcohol level. Figure 1 shows the unadjusted, age and sex adjusted, and multivariable adjusted odds ratios and 95% confidence intervals for the association between unlicensed driving and car crash injury. Unlicensed drivers were at significantly higher risk of car crash injury than those holding a valid license in the unadjusted model (OR 12.1, 95% CI 3.8 to 38.4), and after adjustment for age and sex (OR 11.1, 95% CI 4.2 to 29.7) However, after adding education level, ethnicity, driving exposure, time of day, sleepiness score, year of vehicle manufacture, passenger carriage, seatbelt use, blood alcohol concentration, and travelling speed at time of crash, the increased risk was no longer significant (OR 3.9, 95% confidence interval 0.7 to 22.4). These adjustments had a similar effect when restricted to the subset of participants with complete data. Figure 2.2 shows the proportion of the age and sex adjusted odds ratio for unlicensed driving and car crash injury explained by the confounders we examined. Ethnicity and education level were the two largest contributors, accounting for 47% and 34% of the odds ratio respectively, followed by Stanford sleepiness score (32%), blood alcohol level (25%) and driving exposure (22%).

#### 2.2 Technical review

We referred various online content and documentation on ML from various websites such as opency.org, YouTube, etc. We saw a potential to use the power of ML and OpenCV libraries to develop a meaningful project to authenticate the drivers.

We also visited some educational websites such as geeksforgeeks.com, medium.com, etc. to get general ideas to implement our problem domain by using websites as front-end. We referred a YouTube channel called CodingEntrepreneurs for learning to implement OpenCV libraries in a project using Python.

We consistently visited various educational sites for solving small sub-problems in the problem domain.

#### PROBLEM STATEMENT & OBJECTIVE

#### 3.1 Problem Statement

#### 3.1.1 Problem Domain Description

The problem domain for this project is related to Road Safety and Security.

This project uses the ongoing modern technologies and tools into practice to develop a useful software or website for general public to embed in a vehicle for safety and security.

We see nowadays that some people illegally driving various vehicles, without owning a specific driver's license for themselves.

This system will be helpful for general public by implementing an interface to verify the driver before giving him access to a vehicle. This system would give access to the drivers owning a verified driver's license.

We will be developing a website for accepting driver's license and video feed containing the driver's face for verification. The website is expected to be interactive and simplistic.

The verification system will be developed by the use of specific machine learning algorithm by referring the OpenCV library.

#### 3.1.2 Problem Analysis

We will be using the image in the license and images from the video feed to match together to verify the person in the video feed. For coding this process, we are required to import libraries such as numpy, pickles, OpenCV, etc. for storing data, objects and for training our ML model and for performing other functions.

Then we need to develop a website to serve as a front-end and it would require scripting languages such as HTML and CSS. Also, then we have to develop some Python scripts to process the inputs from user and authenticate the user, which will reflect back to the website.

#### 3.2 Objective

#### 3.2.1 Project Objective

Following are the major objectives of our project:

- Gathering all the information and the tools necessary for building this project.
- Designing a meaningful and simplistic website for efficient usage of the system.
- To design fairly accurate user verification system using OpenCV tools.
- Writing an optimized and robust code for the website design and the internal program.
- To develop our website and its processes as fast, efficient and robust as possible.
- Integrating the website and the internal program.
- Performing thorough testing of the project.

#### 3.2.2 Scope of Project

- We will build our machine learning model using python because it is very interactive and easy to code in case of developing ML models. For the major part we will be using OpenCV library and its tools for training our ML model. There are other various libraries available in python such as pickles, numpy, pandas, scipy, scikitlearn, etc. which are a great help in machine learning.
- Also, we will be using HTML, CSS, and various technologies and some python scripts and libraries such as Flask to develop website and deploy our ML model to website.
- Due to hardware limitations for building ML model, we will be using a relatively small dataset for our model which might not work much efficiently (due to small training set). Apart from hardware limitations, ML models never works fully perfect in every scenario, rather it may improve overtime.
- For most of the time, OpenCV Machine Learning algorithms gives out fairly accurate predictions.

#### **CHAPTER 4**

#### PROPOSED DESIGN AND METHODOLOGY

#### 4.1 Hardware Platform Environment

Following are the requirements for hardware platform environment of the project:

- A working PC or Laptop.
- A working Webcam.
- Processor: Any (Intel, AMD, etc.)
- GPU: Any (Nvidia, AMD, Intel, etc.)
- Memory: min. 1 GB RAM (2 GB recommended).
- Working internet connection (Recommended).

#### 4.2 Software Platform Environment

Following are the requirements for hardware platform environment of the project:

- Operating System: Any Latest (Windows, Linux, etc.)
- Any latest Browser with JavaScript enabled. (Chrome, Firefox, etc.)
- Scripting languages such as HTML, CSS, Python 3, etc.
- Latest Python setup used with certain libraries installed.
- Libraries such as numpy, cv2(OpenCV), pickles, etc.
- Website development environment such as Notepad++ and Google Chrome.
- Development environment such as Anaconda and python 3.
- Web server deployment software (Apache, WAMP, XAMPP, etc.)

#### 4.3 Use Case and Flow Diagrams

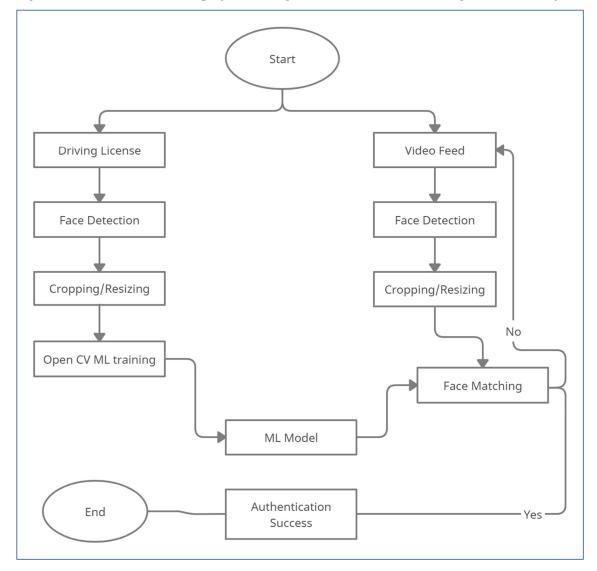


Fig 4.1 shows the DFD for this project and Fig 4.2 shows the Use-Case diagram for the Project.

Fig 4.1 Data Flow Diagram of the project

Fig 4.1 shows the Data Flow Diagram in which mainly two inputs, license image and video feed are taken from user and further processing on the images such as face detection, cropping and resizing of images are performed in real-time. Then the processed images are taken for Model training and face matching, and the process repeats for a certain limit, if face does not match. Otherwise, if match is found, access is granted to the user and the process ends. If match is not found after enough iterations, user is denied to access the vehicle.

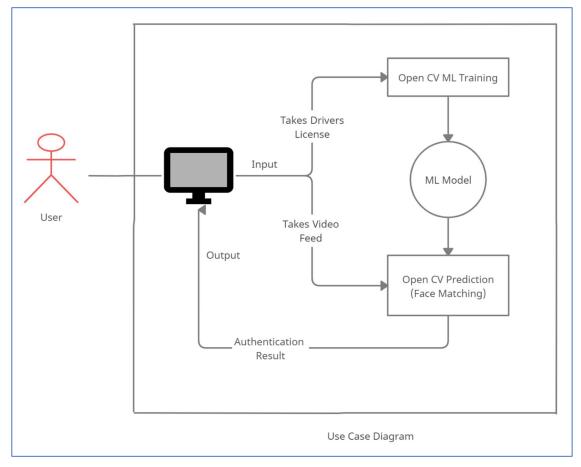


Fig 4.2 Use-Case diagram of the Project

Fig 4.2 shows the use-case diagram of the project, in which the user is asked his driving license first which is processed to train a model by using OpenCV library. Then the user is asked to provide his real-time video feed, which is processed by the machine and is further matched against the trained ML model. Using the results, the program decides whether to authenticate the user or not and displays out the result on the website for the user to see.

#### 4.4 Project Design

#### 4.4.1 Django Web Server

- In this project, Django Web Server is used as backend of the project.
- Since we are required to execute python scripts for the solution of our project, Django turns out to be the best choice as it is designed and written in python.
- Django is one of the best web servers to rapidly develop and deploy web apps and websites.
- Key roles of Django Web Server in our project are:
  - o Deploy our website to the network.
  - o Take user's input.
  - Store the user's data and process it.
  - Run necessary python scripts to process images and yield desired output.
  - o Return the desired output back to the user.

#### 4.4.2 OpenCV and face recognition libraries

- OpenCV and face\_recognition contains necessary methods that can be used to develop and train a Machine Learning model from the license image.
- Then the machine learning model can be further used to match the user's image with the image in the license to verify him/her and provide desired output.
- This output can further be used to verify and grant access to the user.
- These libraries are imported into the python scripts stored in Django Web Server. Certain functions are developed inside these python scripts, that performs the above stated operations with the help of these libraries.

#### 4.4.3 Front-end using HTML, CSS, JS

- Front-end of this project is a website developed using HTML, CSS and JavaScript.
- The structure of the webpages is written in HTML and designed using CSS scripts.
- HTML is embedded with some scripts written in JavaScript which performs following operations:
  - o Turns on the webcam on the user's device.
  - O Captures image/s from the webcam when a button is pressed.
  - o Resets the webcam if needed.
  - o Processes the images for sending them to the server.
  - o Sends the images to the server when Verify button is clicked.

#### **IMPLEMENTATION DETAILS**

#### **Project Codes**

#### settings.py

```
from pathlib import Path
BASE DIR = Path( file ).resolve().parent.parent
SECRET KEY = 'django-insecure-
u&lxgm%j%=o40t&4@q#k&9f+% xcv=iw1!z0wiy3zqz4b-$=4='
DEBUG = True
ALLOWED HOSTS = []
INSTALLED APPS = [
  'django.contrib.admin',
  'django.contrib.auth',
  'django.contrib.contenttypes',
  'django.contrib.sessions',
  'django.contrib.messages',
  'django.contrib.staticfiles',
  'facerec',
]
MIDDLEWARE = [
  'django.middleware.security.SecurityMiddleware',
  'django.contrib.sessions.middleware.SessionMiddleware',
  'django.middleware.common.CommonMiddleware',
  'django.middleware.csrf.CsrfViewMiddleware',
  'django.contrib.auth.middleware.AuthenticationMiddleware',
  'django.contrib.messages.middleware.MessageMiddleware',
  'django.middleware.clickjacking.XFrameOptionsMiddleware',
]
```

```
ROOT URLCONF = 'facerec.urls'
TEMPLATES = [
  {
    'BACKEND': 'django.template.backends.django.DjangoTemplates',
    'DIRS': ['facerec/templates',],
    'APP DIRS': True,
    'OPTIONS': {
       'context processors': [
         'django.template.context processors.debug',
         'django.template.context processors.request',
         'django.contrib.auth.context processors.auth',
         'django.contrib.messages.context processors.messages',
       ],
    },
  },
1
WSGI APPLICATION = 'facerec.wsgi.application'
DATABASES = \{
  'default': {
    'ENGINE': 'django.db.backends.sqlite3',
    'NAME': BASE DIR / 'db.sqlite3',
  }
}
AUTH PASSWORD VALIDATORS = [
    'NAME': 'django.contrib.auth.password validation.UserAttributeSimilarityValidator',
  },
  {
    'NAME': 'django.contrib.auth.password validation.MinimumLengthValidator',
  },
    'NAME': 'django.contrib.auth.password validation.CommonPasswordValidator',
  },
```

```
'NAME': 'django.contrib.auth.password_validation.NumericPasswordValidator',
},

]

LANGUAGE_CODE = 'en-us'

TIME_ZONE = 'UTC'

USE_I18N = True

USE_L10N = True

USE_TZ = True

STATIC_URL = '/static/'

STATICFILES_DIRS = [

BASE_DIR / "static",
]

DEFAULT_AUTO_FIELD = 'django.db.models.BigAutoField'
```

#### urls.py

```
from django.contrib import admin
from django.views.generic import RedirectView
from django.conf.urls import url
from . import views
urlpatterns = [
    path('admin/', admin.site.urls),
    path(", views.home_view, name='home_view'),
    path('save-licence/', views.save_licence_view, name='save_licence_view'),
    path('verify/', views.verify_view, name='verify_view'),
    url('favicon.ico',RedirectView.as_view(url='/static/favicon.ico')),
]
```

#### methods.py

```
from PIL import Image
from io import BytesIO
import re, base64
import cv2
import face recognition
def getI420FromBase64(codec, image name):
  base64 data = re.sub('\^data:image/.+;base64,', ", codec)
  byte data = base64.b64decode(base64 data)
  image data = BytesIO(byte data)
  img = Image.open(image data)
  img.save(image name + '.png', "PNG")
def match faces():
  licface=face recognition.load image file('lpic.png')
  licface=cv2.cvtColor(licface,cv2.COLOR_BGR2RGB)
  realface=face recognition.load image file('vpic.png')
  realface=cv2.cvtColor(realface,cv2.COLOR BGR2RGB)
  encodelic=face recognition.face encodings(licface)[0]
  encodereal=face recognition.face encodings(realface)[0]
  results=face recognition.compare faces([encodelic],encodereal)
  facedis=face recognition.face distance([encodelic],encodereal)
  status='Verification successful' if results[0] else 'Verification Failed'
  return {'results':results[0],'face distances':(1-facedis[0])*100, 'status': status}
```

#### views.py

```
from django.shortcuts import render,redirect
import requests
from . import methods
def home view(request):
       if request.method=='POST':
               print(request)
       return render(request, 'home.html')
def save licence view(request):
       if request.method=='POST':
               licencepic=request.POST['licencepic']
               userpic=request.POST['userpic']
               lpic=open('lpic.url','w')
               lpic.write(licencepic)
               lpic.close()
               vpic=open('vpic.url','w')
               vpic.write(userpic)
               vpic.close()
               methods.getI420FromBase64(licencepic,'lpic')
               methods.getI420FromBase64(userpic,'vpic')
               return redirect('/verify/')
       return redirect(request, '/')
def verify view(request):
       context=methods.match faces()
       licencepic=""
       userpic=""
       with open('lpic.url','r') as f:
               licencepic=f.read()
       with open('vpic.url','r') as f:
               userpic=f.read()
       context['licencepic']=licencepic
       context['userpic']=userpic
       return render(request, 'verify.html', context)
```

#### home.html

```
<!DOCTYPE html>
<html>
<head>
       {% load static %}
       <meta charset="utf-8">
  <meta name="viewport" content="width=device-width, initial-scale=1.0">
       <link rel="stylesheet" href="/static/demol.css">
       link rel="shortcut icon" href="/static/favicon.ico" type="image/x-icon">
       <script type="text/javascript" src="{% static '/webcam-easy-min.js' %}"></script>
       <title>Licence Capture</title>
</head>
<body>
       style="margin: 0; padding: 0; overflow:hidden; background-color:black; list-
style-type: none;">
             <div class="contentarea" style = "float: left; width: 50%; border:</pre>
solid 2px yellow">
                  <div class = "demo1">
                    <div class = "demo2">
                        <b>VEHICLE USER
AUTHENTICATION SYSTEM</b>
                       <div class="imgdiv">
                         <img src="img1.png">
                         <img src="img2.jpg">
                       </div>
                       <div class="instructionsdiv"> <b>
                         STEP 1:- Store your government authorized driving license
picture into the system for verfication by clicking STORE button.
                         </b><br><br><br><br><b>
                         STEP 2:- The system will verify your face against the driving
```

license already stored in the system by clicking a picture when VERIFY button is clicked.

```
</b></div>
                        <div class="buttonsdiv">
                          <button class="button" id="storebutton"
disabled>STORE</button>
                          <button class="button" id="verifybutton"</pre>
disabled>VERIFY</button>
                        </div>
                     </div>
                   </div>
                </div>
              <1i>
                <div class="contentarea" style = "float: left; width: 50%; border: solid</pre>
2px blue">
                   <div class="demo1">
                     <div class="demo2">
                        <div class="camera" id="cameraframe" style="border: solid 2px</pre>
blue;">
                          <video id="video" style="display:block; margin: 0 auto;"
width="480" height="360" autoplay muted>Video stream not available.</video>
                          <div class="buttonsdiv">
                            <button class="button" id="startbutton">Take
photo</button>
                            <button class="button" id="resetbutton">Reset</button>
                          </div>
                          <canvas id="canvas" hidden></canvas>
                        </div>
                     </div>
                   </div>
                </div>
```

```
<form method="post" action="/save-licence/">{% csrf token %}
              <label for="licencepic" hidden>licence pic</label>
              <textarea height='600' width='600' id="licencepic" name="licencepic"
hidden></textarea>
              <label for="userpic" hidden>user pic</label>
              <textarea height='600' width='600' id="userpic" name="userpic"
hidden></textarea>
              <input type="submit" id="submitbutton" value="Submit" hidden/>
       </form>
</body>
       <script>
  (function() {
     var width = document.getElementById('video').getAttribute('width'); // We will scale
the photo width to this
     var height = document.getElementById('video').getAttribute('height');; // This will be
computed based on the input stream
     var storebuttonclicked=false;
    var streaming = false;
     var video = null;
     var canvas = null;
     var startbutton = null;
    var storebutton=null;
     var verifybutton=null;
     var licencepic=null;
     var userpic=null;
     var submitbutton=null;
     function startup() {
       video = document.getElementById('video');
       canvas = document.getElementById('canvas');
       startbutton = document.getElementById('startbutton');
       resetbutton = document.getElementById('resetbutton');
       storebutton = document.getElementById('storebutton');
```

```
verifybutton = document.getElementById('verifybutton');
licencepic = document.getElementById('licencepic');
userpic = document.getElementById('userpic');
submitbutton = document.getElementById('submitbutton');
navigator.mediaDevices.getUserMedia({
     video: true,
     audio: false
  })
  .then(function(stream) {
     video.srcObject = stream;
     video.play();
  })
  .catch(function(err) {
     console.log("An error occurred: " + err);
  });
video.addEventListener('canplay', function(ev) {
  if (!streaming) {
     height = video.videoHeight / (video.videoWidth / width);
     if (isNaN(height)) {
       height = width / (4 / 3);
     video.setAttribute('width', width);
     video.setAttribute('height', height);
     canvas.setAttribute('width', width);
     canvas.setAttribute('height', height);
     streaming = true;
}, false);
startbutton.addEventListener('click', function(ev) {
  takepicture();
```

```
if(storebuttonclicked){
       storebutton.disabled=false;
       verifybutton.disabled=false;
  }
  else{
       storebutton.disabled=false;
  startbutton.disabled=true;
  ev.preventDefault();
}, false);
resetbutton.addEventListener('click', function(ev) {
  clearphoto();
  startbutton.disabled=false;
  storebutton.disabled=true;
  verifybutton.disabled=true;
  ev.preventDefault();
}, false);
storebutton.addEventListener('click', function(ev) {
  licencepic.value=canvas.toDataURL('image/png');
  storebuttonclicked=true;
  resetbutton.click();
  ev.preventDefault();
}, false);
verifybutton.addEventListener('click', function(ev) {
  userpic.value=canvas.toDataURL('image/png');
  submitbutton.click();
  ev.preventDefault();
}, false);
clearphoto();
```

```
function clearphoto() {
       var context = canvas.getContext('2d');
       context.fillStyle = "#AAA";
       context.fillRect(0, 0, canvas.width, canvas.height);
       var data = canvas.toDataURL('image/png');
       try{video.play();}
       catch(e){
               console.log(e);
       }
     }
     function takepicture() {
       var context = canvas.getContext('2d');
       if (width&&height) {
          canvas.width = width;
          canvas.height = height;
         video.pause();
          context.drawImage(video, 0, 0, width, height);
          var data = canvas.toDataURL('image/png');
       } else {
          clearphoto();
     }
    window.addEventListener('load', startup, false);
  })();
  </script>
</html>
```

#### verify.html

```
<!DOCTYPE html>
<html>
<head>
       {% load static %}
       <meta charset="utf-8">
  <meta name="viewport" content="width=device-width, initial-scale=1.0">
       <link rel="stylesheet" href="/static/demol.css">
       link rel="shortcut icon" href="/static/favicon.ico" type="image/x-icon"></script>
       <title>Verification</title>
</head>
<body>
       <h2 align="center">
              {{ results }}<hr>
              {{ face_distances }}<hr>
              {{ status }}
       </h2>
       style="margin: 0; padding: 0; overflow:hidden; background-color:black; list-
style-type: none;">
              <1i>
                     <div class="contentarea" style = "float: left; width: 50%; border:</pre>
solid 2px yellow">
                   <div class = "demo1">
                     <div class = "demo2">
                        <b>LICENCE PIC</b>
                       <img style="display:block; margin: 0 auto;" src="{{ licencepic</pre>
}}" width="480"/>
                     </div>
                   </div>
                </div>
              <1i>
```

#### demo1.css

```
box-sizing: border-box;
.demo1{}
  background: linear-gradient(to bottom right, green, white 150%);
  /*height: 700px;
  width:1515px;*/
  display: grid;
  padding-top: 10%;
  padding-bottom: 10%;
  padding-left: 10%;
  padding-right: 10%;
.demo2{
  background: linear-gradient(to bottom right, orange, white 150%);
  height: 100%;
  width: 100%;
  box-shadow: 0 0 20px #000;
}
.headdiv{
  font-size: 2vw;
  font-family: 'Courier New';
  text-align: center;
  text-shadow: 2px 2px blue;
  color: green;
}
.imgdiv{
  margin-left: 10%;
  width: 80%;
  height: 10%;
```

```
.instructionsdiv{
  width: 80%;
  margin-left:10%;
  float: left;
  margin-top: 10%;
  font-size: 1vw;
  font-family: 'Courier New';
}
.buttonsdiv{
  width: 80%;
  margin-left:10%;
  margin-right:10%;
  margin-bottom:2%;
  float: left;
  margin-top: 2%;
  font-family: 'Courier New';
}
.button {
  margin-top: 5%;
  margin-bottom: 5%;
  background: linear-gradient(to bottom right,blue,white 150%);
  color: black;
  padding: 3% 9%;
  cursor: pointer;
  font-size: 1vw;
  border-radius: 20%;
  margin-left: 5%;
  margin-right: 5%;
```

## **CHAPTER 6**

## **RESULT SNAPSHOT**

```
| Mindows PowerState
| Care |
```

Fig. 6.1 Starting Django web server

In Fig 6.1 A snapshot is provided showing the process to start the Django Web Server on the server machine.

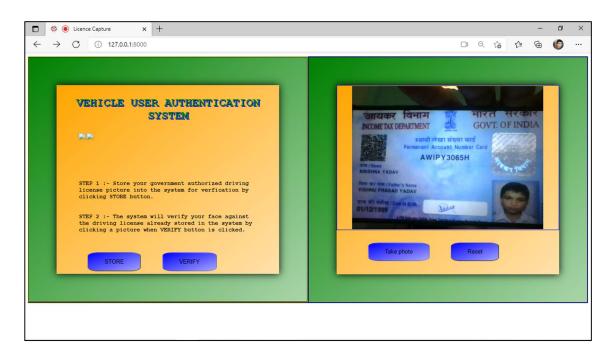


Fig. 6.2 Storing User's ID card

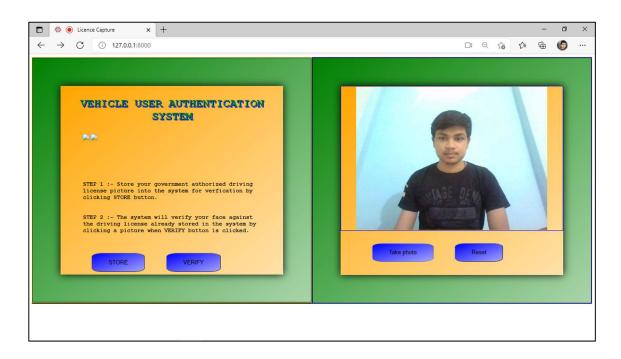


Fig. 6.3 Storing user image

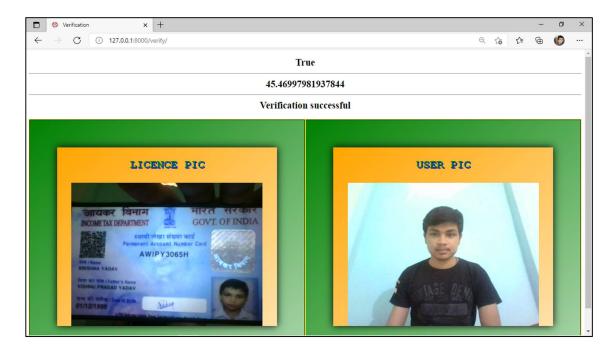


Fig. 6.4 Authentication result

Figure 6.2, 6.3 and 6.4 shows the working of the project in perspective of a user, and shows the step-wise approach to use the website.

Figure 6.2 shows a snapshot of the process to feed user ID to the website. Firstly, user captures the picture of its user ID by pressing Take Photo button, then he/she presses Store button to store that image, in case user wants to retake the photo, Reset button is provided to reset the webcam.

Figure 6.3 shows a snapshot of the process to feed user image to the website. Firstly, user captures the picture of its user image by pressing Take Photo button, then he/she presses Verify button to store that image. Then website automatically submits the photo to the server and then redirects to another page to show the results as shown in Figure 6.4.

Figure 6.4 shows the result after verifying both the images, displaying whether verification was successful or it failed. The images of user ID and user image are also displayed on the result page.

Following Figures 6.5, 6.6 and 6.7 shows another example using a different user ID.

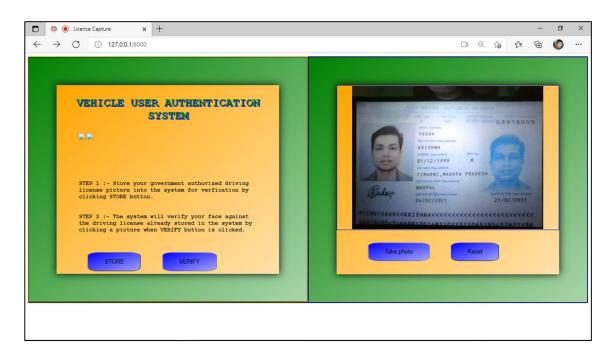


Fig. 6.5 Storing User's ID card

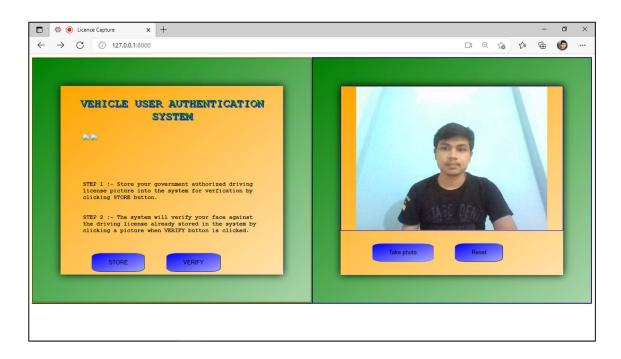


Fig. 6.6 Storing user image

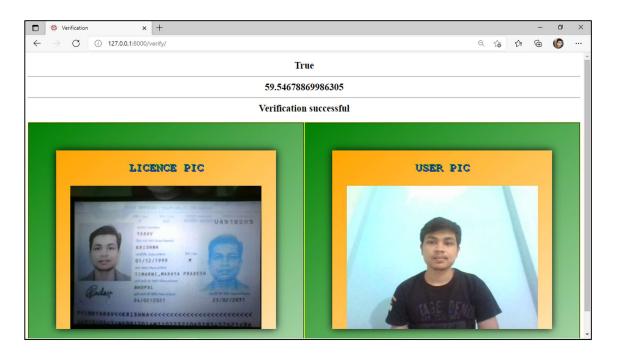


Fig. 6.7 Authentication result

Following Figures 6.8, 6.9 and 6.10 shows the importance of providing a clear image of user ID to the website to successfully obtain desired result.

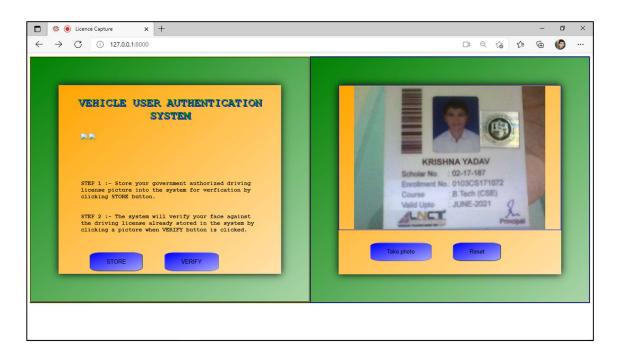


Fig. 6.8 Example of a bad quality user's ID card image

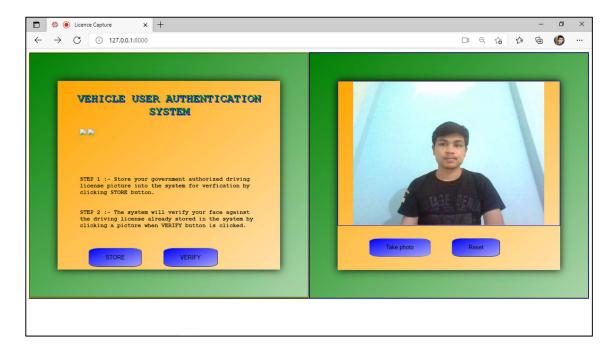


Fig. 6.9 Storing user's image

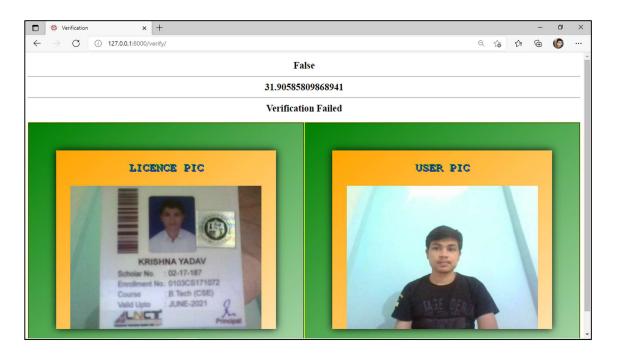


Fig. 6.10 Verification failed due to bad quality image/s

Following Figures 6.11, 6.12 and 6.13 shows that verification is successful when we provide the system with clearer photo of the user ID than the previous ones.

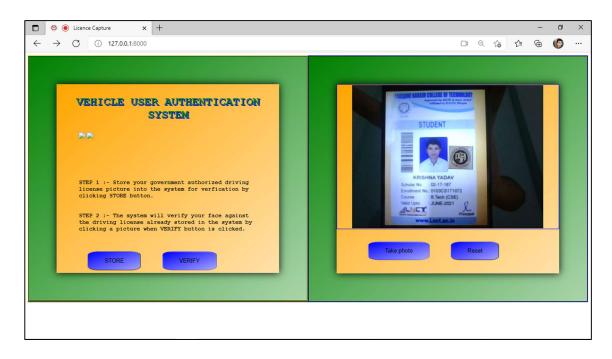


Fig. 6.11 Example of a decent quality ID image

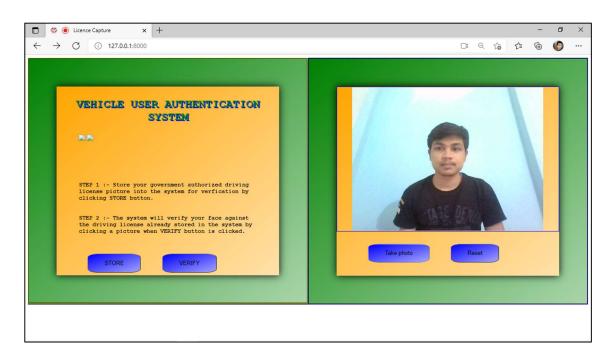


Fig. 6.12 Storing user's image

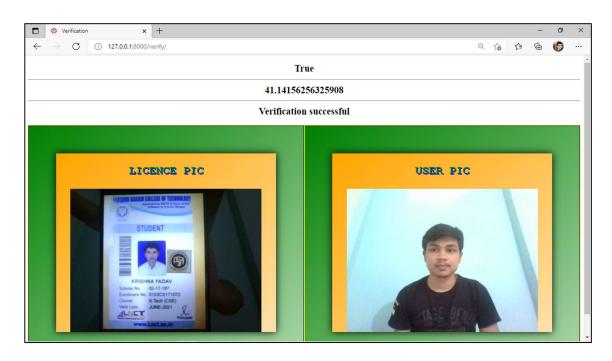


Fig. 6.13 Result of providing good quality images

#### **CONCLUSION AND FUTURE SCOPE**

#### 7.1 Conclusion

With number of people with unauthorized license is increasing it is important to make proper system to restrict people from using vehicle without corresponding license. Though the study reflects that unauthorized license directly effect the accident minorly. But the authorized license ensures the ethnicity and proper safety education which plays a major role in road accidents.

Our system provides a basic implementation of license authentication system. The face recognition unlike password could not be tricked. The vehicle could not be used if the recognized face does not have a valid license in the database. The authentication must be done before starting the vehicle every time. But with face authentication the authentication could be done quickly as the user pushes the start button of the vehicle and have to look at the camera fitted in the vehicle.

The hardware device is easy to install and is affordable. The hardware device is kept to minimum to ensure its affordability and required space in the vehicle. The power required to run the hardware is required once the vehicle start and is very less. Therefore, it won't impact the performance of the vehicle. The website developed to register and authenticate is kept simple to improve its useability. Also, the website is simple clear and interactive and made such that the people with less technical knowledge could use them on their own.

Though there are some possible loops, but this system would make more users to get a valid license and get proper education about road safety. This will help in reducing the accidents and major injuries.

# 7.2 Future Scope

Following key points can add up to the future scope of the project:

- We might embed our solution to Arduino or Raspberry Pi, so that we can test our system on actual vehicles or a simulated environment.
- We might also validate driver's license using online government servers for better security.
- We might also add a functionality to allow only certain person to use vehicle, even
  if they have valid license, so that we can reduce Vehicle Theft.
   We can improve our ML model's accuracy by increasing development
  environment capabilities.

# 7.3 Project Limitations

This project might have following limitations:

- This project only provide solution through website and it does not provide any application for the user. So, it is limited to websites only for now.
- Face detection can be fooled by showing a photograph or similar faces.
- The dataset used in developing the model is relatively small which might affect the accuracy of the prediction of our project.
- Due to hardware limitations of the developing environment, the ML model is less reliable and less accurate.
- In practice, ML model are never said to be always accurate in predicting as compared to actual human being's prediction.

- <a href="https://docs.opencv.org/">https://docs.opencv.org/</a>
- https://github.com/maddevsio/go-idmatch
- https://github.com/CatalystCode/faceanalysis
- <a href="https://github.com/domjhill/Python-FaceTemplateMatching">https://github.com/domjhill/Python-FaceTemplateMatching</a>
- https://www.youtube.com/PmZ29Vta7Vc
- https://www.google.com/
- Websites like www.javatpoint.com, www.geeksforgeeks.com, etc.
- R Datasets (preinstalled with normal installation of R). Each one includes description of variables and sample R code: <a href="https://stat.ethz.ch/R-manual/R-patched/library/datasets/html/00Index.html">https://stat.ethz.ch/R-manual/R-patched/library/datasets/html/00Index.html</a>
- Google Dataset Search: https://toolbox.google.com/datasetsearch
   New (Jan, 2020) Google Dataset Search (25 million datasets): https://datasetsearch.research.google.com/
- NOAA (the US National Oceanic and Atmospheric Administration) operates weather stations that measure surface temperatures at different sites around the United States.
   The hourly readings are <u>publicly</u> available: http://www.ncdc.noaa.gov/qclcd/QCLCD?prior=N
- U.S. Census Data: <a href="https://www2.census.gov/programs-surveys">https://www2.census.gov/programs-surveys</a>
- MovieLens / GroupLens movie recommender system. Research project with choice of recommender algorithms and links to open datasets (Google search listing): <a href="https://www.google.com/search?client=safari&rls=en&q=movielens&ie=UT">https://www.google.com/search?client=safari&rls=en&q=movielens&ie=UT</a>
   F-8&oe=UTF-8
- Boston Housing

  Dataset: http://www.cs.toronto.edu/%7Edelve/data/boston/bostonDetail.html
- Connor J, Norton R, Ameratunga S, Jackson R. (2004) The contribution of alcohol to serious car crash injuries. Epidemiology, Vol. 15, No. 3, pp. 337–344.

- Connor J, Norton R, Ameratunga S, Robinson E, Civil I, Dunn R, Bailey J, Jackson R. (2002) Driver sleepiness and risk of serious injury to car occupants: Population based case control study. British Medical Journal, Vol. 324, pp. 1125–1128.
- DeYoung DJ, Peck RC, Helander CJ. (1997) Estimating the exposure and fatal crash rates of suspended/revoked and unlicensed drivers in California. Accident Analysis & Prevention, Vol. 29, No. 1, pp. 17–23.
- Federal Office of Road Safety (1997a) Profile of unlicensed motorists in fatal crashes.
   Federal Office of Road Safety, Canberra. Federal Office of Road Safety (1997b) Road behavior of unlicensed motorists involved in fatal crashes. Federal Office of Road Safety, Canberra. Griffin LI, DeLaZerda S. (2000) Unlicensed to kill.
- AAA Foundation for Traffic Safety, Washington, DC. Harrison WA. (1997) An
  exploratory investigation of the crash involvement of disqualified drivers and
  motorcyclists. Journal of Safety Research., Vol. 28, No. 3, pp. 213–219. Kim S, Kim
  K.
- (2003) Personal, temporal, and spatial characteristics of seriously injured crash-involved seatbelt non-users in Hawaii. Accident Analysis and Prevention, Vol. 35, pp. 121–130. Knox D.
- (2003) Research into unlicensed driving—Literature review. Department for Transport, London. Knox D, Turner B, Silcock D, Beuret K, Metha J.
- (2003) Research into unlicensed driving: Final report. Department for Transport, London. Land Transport Safety Authority.
- (2000) Stats: Road crash data from the LTSA. Land Transport Safety Authority, Auckland. Land Transport Safety Authority.
- (2003) Disqualified and unlicensed drivers and road crashes: What's the connection?
   LTSA, Auckland. Land Transport Safety Authority. (2004) Getting your car driver license. LISA, Auckland. Perneger T, Smith GS.
- (1991) The driver's role in fatal two-car crashes: A paired 'case-control' study. American Journal of Epidemiology, Vol. 134, No. 10, pp. 1138–1144. Retting RA, Ulmer RG, Williams AF.
- (1999) Prevalence and characteristics of red-light running crashes in the United States.
   Accident Analysis and Prevention., Vol. 31, No. 6, pp. 687–694. Shah BV, Barnwell BG, Bieler GS.

- (1997) Software for the statistical analysis of correlated data: SUDAAN User's Manual, Release 8.0.0. Research Triangle Institute, Research Triangle Park, NC. Shibata A, Fukuda K.
- (1994) Risk factors of fatality in motor vehicle traffic accidents. Accident Analysis and Prevention, Vol. 26, No. 3, pp. 391–397. Statistics New Zealand.
- (2001) Resident population of the Auckland Region, March 2001. Statistics New Zealand, Auckland. Woodward M.
- (2005) Epidemiology: Study design and data analysis. Chapman & Hall/CRC Press, Boca Raton.