PREDICTING BLOOD ALCOHOL CONCENTRATION LEVEL USING HORIZONTAL GAZE NYSTAGMUS ANALYSIS.

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ABSTRACT

Drinking and driving is a primary cause of road traffic accidents (RTAs), which have a high incidence and death rate globally (Houra et al. 2018). Law enforcement units as well as responsible alcohol serving outlets such as restaurants and bars etc. have always used blood alcohol levels to determine the levels of intoxication of a person. This is a particularly important task to ensure public safety as an intoxicated person is not only dangerous to the public but also to himself. Whilst blood alcohol concentration (BAC) prediction has been improved significantly following the adoption of Machine learning (ML) and Deep Learning (DL) techniques, still there remain many challenges such as different methods for HGN analysis to predict accurate BAC levels, improving the dataset and so on. Initially, to predict BAC, police look for specific symptoms including slurred speech, gaze nystagmus, red watery eyes, the odor of alcohol on breath and clothes and so on but among this blood alcohol concentration (BAC) prediction methods are the most popular. Blood alcohol content (BAC) prediction is still an unexplored research subject in the computer vision arena since it presents several obstacles. Then the dataset is not available to explore with different models. Most of the study uses their own volunteers or controlled laboratory test study by any organization. As a result, the goal of this study is to determine BAC from analysis of the Horizontal Gaze Nystagmus (HGN) test. Again, the implementation of the linear regression model will be used to predict the continuous values of eye jerking and BAC level, whereas classification models are often used to predict discrete values, such as whether the person is intoxicated. In a word it can say that this study adopts image processing machine learning techniques for detecting HGN analysis and linear regression model for predicting BAC level.

Keyword: Blood Alcohol Content (BAC), Horizontal Gaze Nystagmus (HGN), regression, ML, DL, Linear regression.

INTRODUCTION:

Lowering the allowable blood alcohol concentration (BAC) for drivers is a popular public health policy employed by governments and jurisdictions worldwide. (Huiqin and Lei 2017). The frequency of road accidents caused by drunk driving has increased considerably in recent years, and Road accidents have ranked among the leading causes of death since 2016 (Colin et al 2019). As a result, it is apparent that intoxicated driving directly threatens to undermine public safety. Worldwide alcohol use is the ninth leading cause of both deaths and injuries, with approximately

12.2% of males aged 15-49 years dying from alcohol-related causes. (ZhenLong et al. 2020; Stanley et al. 2018).

Blood alcohol concentration (BAC) is the commonly used indicator of intoxication, which evaluates an individual's blood alcohol content, and it is measured in gram per decilitre (g/dL). It means how many grams of alcohol is present in 1 decilitre of blood (Colin et al. 2019). BAC can be determined by using technologies that analyse blood, urine, or exhaled breath (Huiqin and Lei 2017). The higher the BAC level, the greater impact on the human body. When BAC goes up than 0.08 it means the suspect will have slurred speech, poor coordination, and slow thinking. He or she cannot maintain lane position and brake properly. In addition, considerable impairment in vehicle control, attention to driving tasks and processing of necessary visual and auditory information can be observed.

Nystagmus is used in medical science to describe the uncontrollable jerking of the eyes. This jerking occurs when a person is drunk. As a result, police officers conduct the horizontal gaze nystagmus test to examine someone's nystagmus and determine whether there is sufficient evidence to make an arrest for drunk driving.

Alcohol can have a broad impact on numerous parts of the main neurological structure, that would hamper vision movements and mental functional areas related to vision. (Silva1 et al. 2017). When someone stares horizontally at an angle greater than 45 degrees, their field of vision is stimulated, which results in an uncontrollable movement of the eye known as nystagmus (Charles et al. 2019). The HGN test is built on the concept that alcohol affects the eyes' automatic tracking systems (Shadi et al 2018). Alcohol reduces the eyes' capacity to detect objects quickly and makes them jerk earlier than they might in a non-drinker, but If jerking occurs when every pupil keeps moving horizontally before reaching a 45-degree angle of view, the blood alcohol concentration is. 08 or more (Marjorie et al 2019).

LITERATURE REVIEW

ML and DL approaches have garnered much attention in the BAC prediction from the eye movement field, and many researchers have realized the importance of studying BAC prediction from HGN analysis. for this study, acquiring HGN analysis information is an essential step in BAC prediction since eye movement analysis can improve overall BAC prediction performance and which is critical when it comes to security BAC prediction systems. The following sections will discuss the limitations of the literature with regard to applying ML and DL models for AG and analysis and back predictions.

A. MACHINE LEARNING-BASED BAC DETECTION

B. Suoletto et al. (2019) applied machine learning, Logistic regression models and it is observed smartphones have been shown to be able to record distinct gait patterns that are sensitive to intoxication from alcohol, identifying intoxication within persons with an accuracy of about 90%. However, the drawbacks are its limited sample size, the use of a cohort that drank primarily in moderation and the controlled data measurement settings.

Then to forecast a person's Blood Alcohol Concentration (BAC) from their smartphone's accelerometer and gyroscope data, Li et al. (2021) implement regression analysis by using Bi-directional Long Short-Term Memory (Bi-LSTM) and Convolutional Neural Network (CNN) architecture. The model performs 86.7% accurate.

Huiqin and Lei (2017) executed classification with a support vector machine (SVM) classifier. SVM classification successfully distinguished drunk driving from regular driving with an accuracy of roughly 93%. The samples used in this investigation included university students. The trained SVM could be employed as an automatic drunk driving detection approach because it was created as an early warning drunk driving detector.

Suoletto et al. (2018) applied machine learning model to predict BAC during drinking episodes. But their dataset was very small and missing gait task data. Task completion was paid, which probably unnaturally inflated success percentages. App is only available for iOS devices and a possible error with the alcohol

B. DEEP LEARNING-BASED BAC DETECTION

Charles et al (2019) develop a mobile app based on CNN-RNN deep learning model. Swift and gamification were utilized in their study to analyse the HGN test and BAC level procedures. To obtain a sequence of curves, they attempted to follow the tester's pupil's movement. Then researchers created three models to compute and examine the curve for the HGN test's three sub steps. Finding a suitable dataset with labels to train the algorithm was one of their challenges.

An approach using physics-informed neural networks (PINNs) to predict the blood alcohol signal from a transdermal alcohol signal was put out by Oszkinat et al in 2022. For transdermal alcohol transport in the human body, a diffusion formula model is implemented and to estimate the distribution of unknown parameters more accurately, a generative adversarial network (GAN) with a residual-augmented loss function is used. The approach might forecast the blood alcohol concentration and measure the risk in the form of conservative error bars based on the distribution of the unknown factors. In addition, they demonstrate how these conservative error bands can be made more precise by using a posterior latent variable.

RESEARCH QUESTIONS

1. What features to include to predict the intoxication level of drug consumption from the subject's eye movement?
2. What machine learning techniques can be used to predict the intoxication level of drug consumption from subjects' eye movement?
3. How can the proposed model be evaluated?
4. What methods of evaluation can be adopted for evaluating the proposed model?

METHODS:

Participants and data collection:

Most of the study uses their own volunteers or controlled laboratory test study by any organization. Since the supervise machine learning method is used in this project, data with labels must be collected. And data should be the records of eye movement from users who are not drinking and drunk. So, the test results that were published in the publication "Robustness of Horizontal Vision Nystagmus Test" (Burns and Marcelline 2007) by the U.S Department of Transportation (National Highway Traffic Safety Administration) are used as data. But the publication test result data was not sufficient so sample videos for eye movements were collected from a website called "The Horizontal Gaze Nystagmus Test: DUI Investigation and Flood Science in American Courts" and processed by a developed algorithm to collect data and enrich the dataset. According to (Burns and Marcelline 2007), in their study officers tested HGN 4 times on each of the 9 participants and 9 participants provided 36 HGN scores data of a standard stimulus distance. Fig 3.2 indicates a sample of the dataset. In this project these test results have been used as dataset and there is four-column in the dataset and all the columns are selected for the experiments, which are the BACs (g/dL), exam, participant’s BAC (g/dL) and jerking amount. The participants are asked to drink a certain amount of alcohol. After 30 minutes of consuming the alcohol the examiner tests HGN and participant BAC level.

Methodology:

The primary approach of this research is focusing on (BAC) Level detection and the relevant techniques for BAC such as HGN test. A suspect must track the movement of a stimulus with their eyes during an HGN test (Charles et al. 2019), as well as the impacts of changes in the stimulus' movement speed and its elevation above eye level. Then the distance between the stimulus and the face is measured. So, followed by the HGN test mechanism, this is how the prediction of blood alcohol concentration (BAC) level from eye movement is analyzed.

This study adopts image processing machine learning techniques for detecting HGN analysis and linear regression for predicting BAC level. And the objective of this study is to predict the intoxication level of drug consumption from the subject's eye movement analysis. And to evaluate the proposed machine learning model by means of evaluation metrics. The study also aims at the improvement of eye analysis methodologies using machine learning techniques and accurately detect nystagmus or jerking over eye movement.

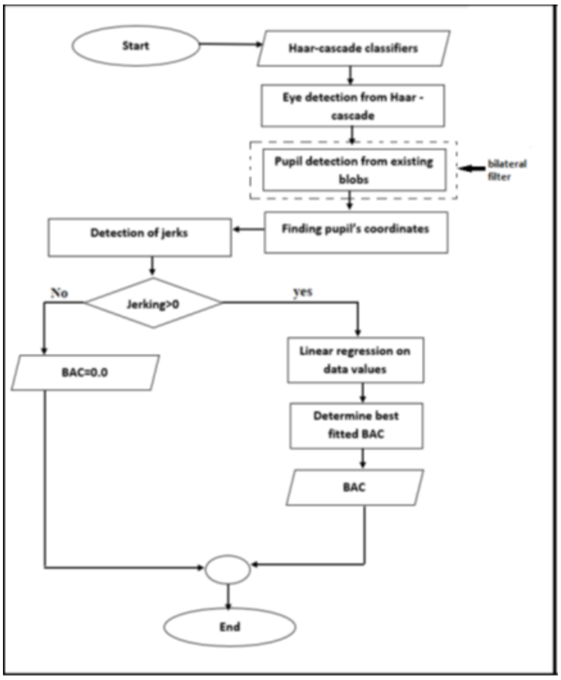

Figure 1: Proposed development framework

Figure 1 shows the proposed framework for the development stage. The development stage consists of four steps-

a) Haar cascade classifier for eye detection,
b) Pupil detection from detected eye,

c) Jerking detection over eye movement and

d) Finally, develop a linear regression model for predicting BAC level.

a) HAAR CASCADE CLASSIFIER FOR EYE DETECTION:

The most effective way to identify an object is to use the Haar cascade classifier, which Paul Viola and Michael Jones presented in their 2001 paper "Rapid Object Detection with a Boosted Cascade of Simple Features". The Haar Cascade algorithm uses edge or line detection features.

In this project, modified haar cascade is used to detect eye and the modified Haar cascade algorithm's steps as follows in figure 2. It is modified haar- cascade because (Paul Viola and Michael Jones 2001) uses positive images (images of faces) and negative images (images without faces) to train the classifier. In this project, positive and negative images mean image with a background and the image of without background are used with a non-linear bilateral filter to train the classifier to generate XML file. By applying this filter, images can be improved by the modification of improbable values by rejecting data from smoothing areas and spatial frequency components that are too small.

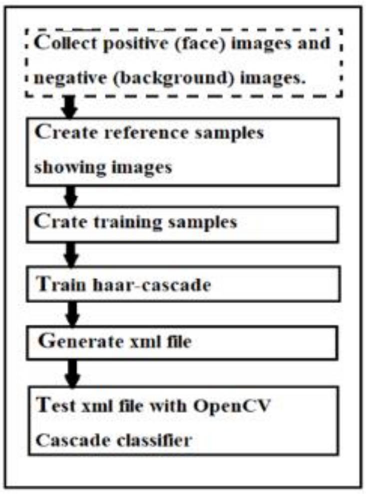

Figure 2: The modified Haar cascade algorithm's steps

When a new image of an object comes, the classifier tries to best fit the object image into the training classifier. Different parameters are used to define the best fitting limits. The train data images are then transformed into xml file for faster calculations. These xml files can be used as train data in several types of platforms.

For this project, xml file is generated for eye haar cascade classifier as the training data for all types of eye images. Then the cascade xml file is trained over several eye images for confirmation of 100% detection. Once it is fully trained, the xml file is finalized as training data.

b) PUPIL DETECTION FROM DETECTED EYE:

Once the eye is detected using the eye haar cascade xml, OpenCV equalizeHist method is used, which is basically create a copy of image frame from the original frame with specified dimension. After separating the eye frame from the full video frame for analysis of high image processing, it can run over low processor power such as mobile platforms. Then OpenCV bilateral Filter is implemented to blur the eye frame to have the pupil area more precise.

If a pixel value is lower than thresh value it is considered as 1(white), else is considered 0(black). But different people have different pupil colors. Then, the thresholding method is implemented to generate the binary image of the blurred eye to have the specific position of the pupil.

After having the binary image, the OpenCV minimum enclosing circle methodology is applied to reduce noise and generate a more precise result of the pupil position. Then a red circular dot is created over the original pupil image frame for checking the precise location of the pupil and the coordinate is preserved as a location of the pupil's position.

When the circle's radius and center's x, y coordinates are extracted, then amongst all the radius and coordinates the biggest radius is selected as pupil's radius. The coordinate of the biggest radius is isolated from all other noises occurred for per frame. The rest of the circles are considered as noise and are ignored from the frame for easier and faster calculations. Anyway, only the pupils generally have the most perfect circular shape. So most promisingly, the pupil will have the biggest enclosing circle to cover its circular shaped area. Once pupil is decided from the noises, the center coordinates are updated as the position of the pupil in the image or video frame.

c) JERKING DETECTION OVER EYE MOVEMENT:

After having all coordinates of the captured video of the eye, jerking detection method is run to find out the amount of jerking that occurred. There are minimum pixel distance and maximum pixel distance in the method where the method will check the pupil coordinate between minimum and maximum distance and determine where the jerking occurred.

Once the most promising pupil's positions are calculated, the whole stack of the X coordinate is passed for jerking analysis. In this project, the coordinate is passed in a function named jerking detecting, which take array of coordinates, min distance of jerking and maximum distance of jerking as parameter. According to Burns, Marcelline (2007), minimum distance is set to 8 pixels and maximum distance is set to 12 pixels because jerking occurs within a very short distance of pixels for a very short period and between 8-to-12-pixel distance the most perfect jerk occurs. Jerking can occur at minimum distance 5 to 12 (Burns and Marcelline 2007) but to avoid false jerk reading for this study 7-to-12-pixel distance is counted.

So here firstly, the function determines the midpoints of all X coordinates given, by finding the minimum X value and maximum X value. After this, the coordinates which are bigger than midpoint are considered as right side, smaller than midpoint are as left side for both eyes. Then, the coordinates are assembled in list for analysis of jerking. For the right side, if the next coordinate is bigger than previous coordinate, the previous coordinate is pushed into the list for further analysis. When the next coordinate is less than previous coordinate, list distance is calculated using this formula:

Distance = last coordinate of list - first coordinate of the list.

After calculating the distance if the distance is bigger than minimum distance (by default 8) and smaller than maximum distance (by default 12), the distance is considered as jerking. The list is erased for new coordinate pattern. Same process is done for jerking detection of left side eye in vise versa.

d) DEVELOPING LINEAR REGRESSION MODEL FOR PREDICTING BAC LEVEL:

In this project sklearn Linear Regression model is used to predict the BAC level from the jerking amount. After having the total jerking amount, the jerking amount is passed to the data analysis method. Because of insufficient data, it is planned to create its own dataset by running videos by developed algorithm and gathering the result in a CSV file to enrich the dataset for better ML model performance.

The concept of regression is implemented based on two ideas. Firstly, regression analyses are frequently used for forecasting and prediction. Secondly, in some conditions, causal relationships between the independent and dependent variables can be found using regression analysis. (Dastan and Adnan 2020).

RESULTS & DISCUSSION

EYE DETECTION AND PUPIL SHAPE ANALYSIS:

The figure 3 indicates the separated detected eye using Haar cascade classifier and In Figure 4 shows the detected eye after applying blurring effect. The red line box of figure 3 is the detection sign of eye. Only the eye is separated from the video frame for the noise reduction of pupil detection and less analysis for high image processing so that it can run over low processor power. A blurring effect has been implemented on the eye frame to have the pupil area more precisely.

Figure 3: Detected eye using Haar cascade classifier.

Figure 4: Detected eye with blurring effect.

Again, figure 5 demonstrates the detected pupil's radius which is obtained after implementing the threshold method to generate the binary image of the blurred eye and to have the specific position of the pupil. Generally, the pupils have the most perfect circular shape and detected biggest radius is known as pupil's radius. That's why only the coordinates of the biggest circular radius are isolated from all other noises that occurred per frame and the rest of the circles are considered noise and are ignored from the frame for easier and faster calculations.

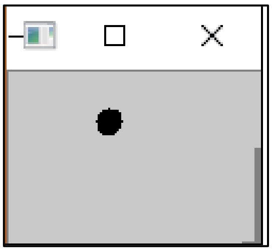

Figure 5: Detected pupil's radius.

PUPIL DETECTION RESULT:

Figure no 6 shows the result of detected pupils. As seen there is a red box frame. In this red frame, it is detected if there are any image and pixel coordinates (height and weight) of the detected eye. Again, there is a blue line right in the middle of the box because the pupil is always in the center of the eye, and it is needed to find the pupil on that line. If a black object (considered as pupil) is detected on this blue line, it is tried to find whether the black object is circular radius. These circular objects are called contours. Amongst all the circular radius and coordinates, the biggest circular radius is selected as the pupil's radius. And lastly after pupil detection, it is marked with a red dot as shown in the figure.

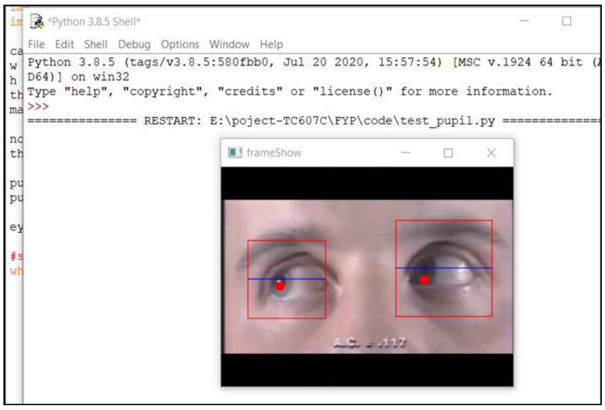

Figure 6: Detection of pupil's location coordinate

JERKING DETECTION RESULT ANALYSIS:

As shown in Figure 7, a red circular dot is set in the original pupil image frame to check the precise position of the pupil, and there is x, y coordinates, which are preserved as the pupil position coordinates. The numbers 68, 68, 71, 71, 69 and so on are the pupil coordinates. But now, if one of those numbers suddenly jumps or drops from the previous number, it is considered a jerk. Once all the coordinates of the captured video of the eye are gathered, the jerk detection method is executed to find out the amount of jerk that has occurred.

According to National Highway Traffic Safety Administration (Burns and Marcelline 2007) there are minimum pixel distance and maximum pixel distances in the method to detect jerking. Here the method will check the pupil coordinate between a minimum and maximum distance and determine where the jerking occurred. The minimum distance is set to 8 pixels and maximum distance is set to 12 pixels, as jerking occurs within a very short distance of pixels for a very short period, but jerking can occur from minimum distance 5 to 12 pixel (Burns, Marcelline et al. 2007). It cannot be selected as a jerking if the minimum distance is less than 7 and the maximum distance is 12. So, after calculating the distance, if the distance is bigger than the minimum distance (by default 7) and smaller than the maximum distance (by default 12), only then the distance is considered as jerking. the first jerking detection analysis shows that the pupil coordinate jumps from 72 to 82 because here the distance of two-pixel coordinates is 10 which is between 8 and 12 according to the formula (Burns and Marcelline 2007). Similarly, the rest of the jerking's are detected.

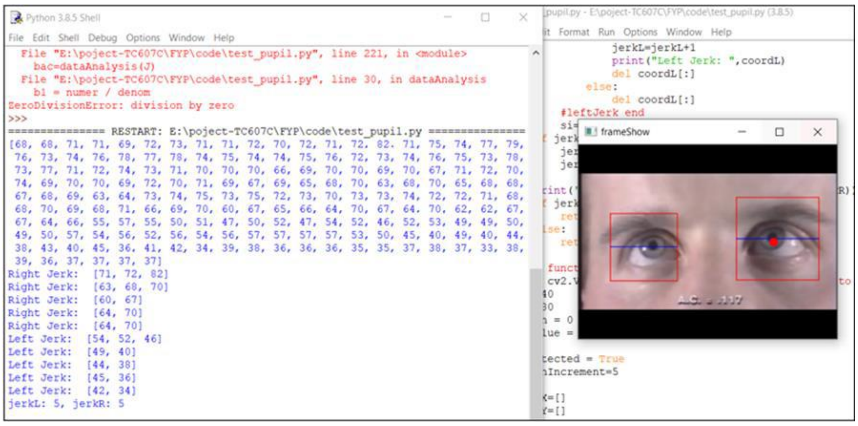

Figure 7: Coordinates results of jerking (modified).

Again, in figure 8, the values of coordinates are shown through a scatter plot, and it is visible that when the coordinates values suddenly jump or drop from the previous values, which is considered a jerking.

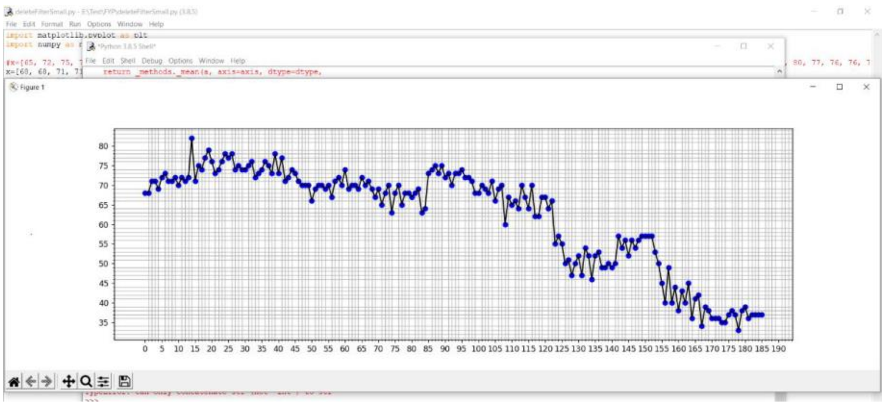

Figure 8: Jerking Scatter plot

LINEAR REGRESSION RESULT ANALYSIS:

Once the total jerking amount is collected, the jerking amount is passed to data analysis method. This method uses sklearn Linear Regression model to predict the BAC level from jerking amount. The most common metric for evaluating linear regression model performance is called root mean squared error, or RMSE (Dastan and Adnan 2020).

The basic idea is to measure how good or bad the model's predictions are when compared to actual observed values. In the same way, regression performance quantifies the strength of a regression model to make predictions that are close to the true values. Again, the lower values of the RMSE and the performance score equal to 1.0 indicate better fit of the model (Dastan and Adnan 2020) and this study has achieved 0.02479 for RMSE score and .825 for models' performance score.

Additionally, coefficients in regression model analyses indicated the types of correlations and relationships that are mathematically significant in the model (Dastan and Adnan 2020). If the Correlation Coefficient is equal to +1, it means perfect positive relationship (Dastan and Adnan 2020). This model's Correlation Coefficient is 0.79

Furthermore, in figure 9, all the data of dependent and independent variables named as participant_BAC and jerking is demonstrated to show the best fit line of the linear regression for this research. This best fit line refers to a line through a scatter plot of data points that articulates the relationship between predicted values and true values.

A solid red line is shown in the figure 9 that line represents the best-fit linear regression line between the dependent variables (participant_BAC) and independent variables (jerking). Again, it is a straight red line because it is a simple linear regression analysis. On the other hand, if this were a multiple regression involving multiple related variables, then a curved line would be formed.

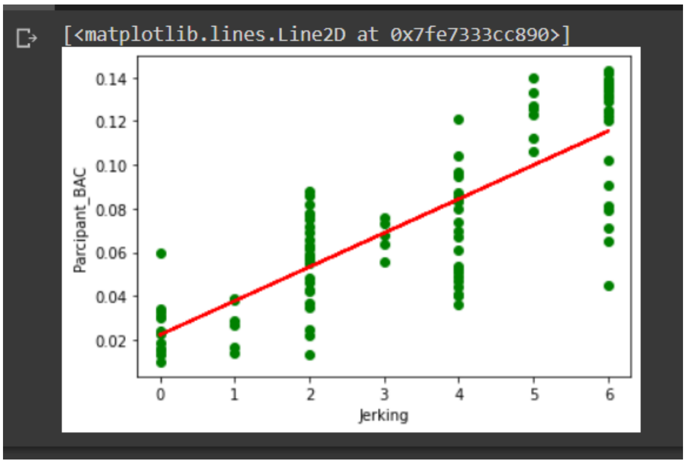

Figure 9: Best fit line of the LR model of the study.

COMPARISON WITH OTHER REGRESSION TECHNIQUES:

The root mean squared error (RMSE) metric, which measures the outputs of a model's departure from the raw data and is one of the most popular measures for assessing the quality of predictions, was used to compare linear regression with decision tree regression, random forests regression, and other types of regression.

Again, calculating RMSE is extremely helpful to have a single number to judge a model's performance. Since the lower values of the RMSE indicate better fit of the model, so after observing the table it is get lower RMSE value for linear regression than decision tree regression and random forests regression model.

One of the most popular and straightforward regression algorithms in machine learning is linear regression (Pedram et al. 2017). It is a method of performing statistical research. In this statistical research methods, linear regression is frequently employed and permits continuous, real, or mathematical variable projections and allows for the measurement of projected effects and their modeling against a variety of input variables. Because it can perform well on a little dataset, a linear regression model was used for prediction in this investigation.

According to the RMSE result, for this study, linear regression performs better than decision trees and random forests because this project’s dataset is a small dataset and consists of only two types of variables which produces a single-tree model. The single tree-based models are very sensitive to data variations, so random forests and decision trees can overfit the data with only one tree (Li, Zou et al. 2020).

Again, If the RMSE score is greater than 1, it means both are overfitted models (Li Balakrishnan et al. 2021). random forests and decision trees RMSE score is 1.19 and 1.32 respectively which indicates overfitting. But when it is added trees to the random forest or decision tree then the tendency to overfit should decrease. In addition, linear regression performs better because the features of linear-regression models are well understood and can be trained very quickly.

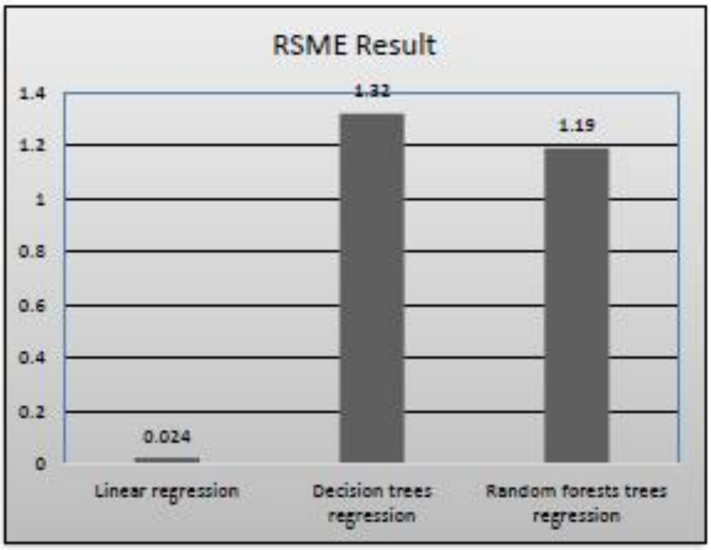

Figure 10: RMSE results of regression models.

COMPARISON WITH EXISTING MODEL:

Li et al. (2021) investigated drinkers' intoxication levels from gait analysis by using neural networks to analyze sensor data gathered from smartphones. And by using the privet investigated gait analysis data, regression analysis of different types of machine learning and deep learning models called Random Forest, LSTM, Bi-LSTM, MLP and CNN architectures is performed to predict a person's Blood Alcohol Concentration (BAC) from gait analysis. Table 1shows the pipelines and best results achieved in the paper (Li, Balakrishnan et al. 2021) using each type of BAC regression model.

RMSE	LSTM	Bi-LSTM	CNN	MLP	RF
Result	.0168	.0167	.0168	.0170	.0243

Table 1: RMSE results of existing model based on gait analyzed data (Li, Balakrishnan et al. 2021).

On the other hand, this study uses different datasets because of the unavailability of datasets and different concepts. Most of the research uses the privet investigated data. Li, Balakrishnan et al. (2021) data is based on the effects of alcohol on a drinker's gait (walk) analysis, whereas this project is based on bac level prediction with

jerking analysis. So, for the comparison, this study's dataset is trained with their one of the models called LSTM and obtain 0.36 RMSE score for LSTM shown in figure no 4.6. LSTM model also performed well on this study's dataset as the lower values of the RMSE indicate better fit of the model [Dastan and Adnan 2020]

LIMITATIONS

One fundamental limitation of this research is pupil detection in the nighttime environment. This project is supposed to be used during nighttime when most of the drunk cases occur. Considering nighttime, the thresh value and other variables are designed to have lower values. So, direct focus of light over the eye can cause error of detecting pupil and determining the BAC level.

Another limitation is this study lacked a proper dataset. As there was no availability of drunk people, the dataset was not a real-world representation of drinking situations, and which has an unsatisfactory effect during regression model building and analysis.

The results of this project were also not compared to benchmark models and algorithms due to the limitations of obtaining those models and algorithms. Although this may affect the validation for the proposed model, it does not impact on the validity of the result as data augmentation methods of generating synthetic data were applied.

FUTURE WORK

Future academics can expand on this study, and some recommendations can be put into practice to make it better. These strategies will be covered in this section, which is- Currently, this project only runs on computers. It is not available for mobile platforms. So, in future, this project can be executed on a mobile platform. And researchers can focus on using different methods to improve pupil detection at nighttime. Then another future work for this project would be to compare the proposed model to benchmark models.

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