

Drugged Eye Detection using Image Processing

Dr. Siddartha B K¹, Divya N B², Rakshitha N B³, Varsha Y J⁴ and Varshini K S⁵

¹⁻⁵Department of Information Science and Engineering, Adichunchanagiri University, BGS Institute of Technology, BG Nagara, Karnataka

Abstract—Drugs are the substances that change a person's mental or physical state. Illegal drugs leads to the major problem to our society. Drug users are now recognized by the use of biological samples, such as blood and urine samples, which is invasive and inconvenient, and it takes more time to get a result.

This research provides a KNN based picture manipulation method for distinguishing drugged and un drugged eyes. The investigation of non-invasive techniques for automated drug usage detection is driven by KNN. The K-Nearest Neighbours algorithm is used to classify sclera patterns according to their similarity to known drug use patterns. It can also estimate the intoxication level of drugs from images by analyzing the variations in the sclera's colour and pattern. Gathering and analyzing input images, Refining and extracting key features from the images are the important process in the Proposed method. Identifying and highlighting the reddened areas, Validating the trained model and showcasing the results, We tested the technique on eyes under the influence of drugs at various stages, both pre- and post-consumption, The objective is to extract the white area of the eye from the supplied image. Training data included images of both drug-influenced and healthy eyes. We experimented with various color models by applying them to the images. the Local Binary Pattern was both used in the model construction for feature extraction.

Index Terms— Drugs, KNN, Sclera, Feature Extraction.

I. INTRODUCTION

Drug addiction is not a disease its a psychological problem that causes compulsive drug use. Illegal substances like heroin and opium are bad for our bodies, doctors do not prescribe them. This is what we are talking about when we discuss illegal drugs. According to the poll, there are 8.75 million cannabis users in India, two million opiate users, and 0.6 million sedative or hypnotic users. There are four main ways that drugs enter our bodies: orally, through injection, through snorting, through smoking. When identifying the drugged eyes in the input image, KNN consider a part called sclera, or the white outer layer of the eye.

Drugs have the potential to cause significant losses in a variety of enterprises. Knowing what is being observed is crucial to determining what controls to implement the following year in order to stop losses. However, due to the inherent variability of the white portion of the eye in different eye types, the wide range of defect kinds, and the presence of red patches, defect detection remains difficult. It is crucial to keep a watch on the reddish area within an eye since visual patterns of distinct sorts is used to determine eye study.

A drug user could get "intoxicated". People who are intoxicated perform risky things. They are not able to operate machinery or drive safely. When a person consumes too much medication, they overdose. Overdosing carries serious risks. It may result in demise. It is simple to overdose on certain drugs, such as aspirin, heroin,

and alcohol. It is more difficult to overdose on other drugs (cannabis, LSD). Many medications have long-term (permanent) negative effects on health.

K-Nearest Neighbor is based on the supervised learning method. The K-NN algorithm places the new case in the category that most closely resembles the existing categories based on the assumption that the new instance and its data are comparable to the examples that are already accessible. The K-NN method categorizes a new data point according to similarity after storing all the relevant data. This implies that the K-NN algorithm can quickly classify newly discovered data into a well-suited category. Although the K-NN technique is primarily used to solve classification problems, it is also used to solve regression difficulties. Since K-NN is a non-parametric technique, it doesn't make any assumptions about the underlying data.

II. RELATED WORK

The authors of paper [1], The meteoric rise of biometric recognition in diverse applications over the past two decades can be attributed to its alluring combination of high accuracy and user convenience. However, despite its proven efficacy, concerns related to security, privacy, bias, and the mysterious black-box nature of decision-making have cast a shadow over the technology. Fortunately, the authors of this paper shed light on these critical issues by providing concise overviews and highlighting avenues for future research. For each concern, they meticulously review existing solutions, identify remaining challenges, and propose strategies for overcoming them. Ultimately, their aim is to guide the biometric community towards designing systems that foster trust, justice, and enhanced security for all. The authors firmly believe that reliable and accurate automated person identification is vital for numerous areas, ranging from national security to everyday transactions. Biometric recognition emerges as a prime contender for this crucial need, potentially surpassing the capabilities of even the most skilled human recognition systems. Yet, its path to reliable deployment hinges on resolving a multitude of outstanding challenges.

To bolster the trustworthiness of biometrics, the authors pinpoint five key research areas demanding immediate attention: security, explainability, fairness, robustness, and privacy. In each domain, they meticulously introduce the problem, emphasize its significance, acknowledge past efforts, and then advocate for deeper investigation. Addressing these crucial factors head-on holds the key to unlocking the full potential of biometric identification, benefitting users, researchers, and policymakers alike. The authors propose a pragmatic "Grand Challenge in Trustworthy Biometrics" as a roadmap for fostering more reliable systems. Envisioning a competition organized by a body like the NIST, they suggest evaluating biometric systems across the five defined categories. Systems meeting predefined quantitative thresholds in each category could be certified as "trustworthy," empowering users to make informed decisions based on both accuracy and reliability.

The authors of paper [2] Working weird hours (shifts) can mess with your sleep and lead to health problems, both physical and mental. Shift workers often struggle to fall asleep and stay asleep, catching 20-42% fewer than regular day folks. This sleep deprivation tanks their productivity at work and spills over into their social lives. In a desperate attempt to cope, many turn to alcohol. Unfortunately, it's a bad mix – booze messes up sleep even more and makes you feel drowsy on the job. This review aimed to figure out exactly how strong the link between shift work and drinking is. The researchers scoured through tons of studies on the topic, digging deep into databases like PubMed and PsycInfo. Sadly, there weren't any comparing shift workers directly to their day-shift counterparts. But what they find was pretty telling. Among 14 studies, six clearly pointed the finger at alcohol when it comes to shift work, especially for those using it to catch some shut-eye. This fueled a debate about whether specific types of drinking, like binge-drinking, were more closely linked to night shifts and rotating schedules.

The authors suspect that folks turn to alcohol as a self-medication for sleep woes and the stress (and other not-so-fun stuff) that comes with working odd hours. Nurses over 50 seem to be particularly vulnerable. This highlights the need for better ways to handle sleep problems – ditching the booze bottle as a sleep aid being a big priority. Shift work often means sleep troubles, tiredness at work, less time for friends and family, and stress. No wonder more shift workers than your average day-jobber reach for the liquor. Four studies confirmed this across different professions, from nurses to factory workers to doctors in the ER. The researchers define "heavy drinking" as five drinks in a row for women and seven for men.

According to authors research [3], Iris recognition is gaining traction in the biometrics world for its unique and stable features. While various texture analysis methods exist, their full potential for improving identification accuracy hasn't been fully explored. This study tests four ways to analyze the squiggly patterns in iris images for person identification.

Fast Fourier Transform (FFT), Discrete Cosine Transform (DCT), Log-Gabor filters, and Haar wavelets – to determine their effectiveness in iris authentication. They saw which one works best at telling different people apart without making mistakes, while also being fast and efficient. We might even mix and match these methods to get even better results!

FFT: Captures spatial frequency information, highlighting prominent patterns in the Iris texture. DCT: Identifies dominant spatial frequencies while compressing data, making it efficient for large datasets. Log-Gabor filters: Mimic the human visual system, extracting local texture features at different orientations and scales. Haar wavelets: Analyze the image at various resolutions, capturing both coarse and fine-grained texture details.

According to authors paper [4] This research explores a new way to check by focusing on the tiny changes in your pupil size when you see light. They built a special camera to capture these super-fast changes and studied how pupils react in 25 people. The results are promising and could help make iris scanners even more secure!

Image Integration: Consider including an image of an iris with highlighted pupil regions to illustrate the focus of the study. Show a simplified diagram of the custom capture device setup used in the research.

The authors of paper [5], Modern medicine has developed powerful drugs to treat many diseases, but some of these drugs can have harmful side effects on the eyes, especially the retina. The retina is a thin layer of tissue at the back of the eye that is responsible for sending visual signals to the brain. It is very sensitive to drugs because it has a rich blood supply and high metabolic activity.

This paper discusses the importance of a special type of eye exam called ultra-widefield (UWF) imaging for diagnosing drug-related retinal toxicity. UWF imaging allows doctors to see a much wider area of the retina than traditional eye exams, which is important because many drug side effects occur in the peripheral (outer) parts of the retina.

Early detection of drug-related retinal toxicity is important because it can allow doctors to stop the drug before it causes permanent vision loss. UWF imaging can help doctors detect these side effects early, even before they cause any noticeable symptoms.

In conclusion, UWF imaging is a valuable tool for diagnosing drug-related retinal toxicity. It can help doctors protect patients' vision by allowing them to detect and stop harmful side effects early.

The authors of paper [6] research explores two ways to use thermal images to identify people who are drinking.

Tracking Heat Clusters: Imagine each person's "heat signature" as a group of dots on a map. As someone drinks, their heat signature "moves" on the map. Researchers found this movement followed similar patterns for many people. This "drunk zone" on the map is used to identify if someone has been drinking.

Checking Specific Hot Spots: Certain areas on the face, like the nose and mouth, get warmer when someone drinks.

This research identified these hot spots by comparing thermal images of sober and drunk people.

By checking just these hot spots, you can potentially tell if someone has been drinking, even without a "sober" image for comparison.

Both methods show that drunk people have different thermal patterns than sober people, especially in the specific areas of face. This is useful for developing tools to detect drunk driving or help identify people who have consumed alcohol.

III. METHODOLOGY

The existing system identifies the infected eyes and drugged eyes by CNN-based image processing technique .In existing system the result of the drugged eye is only based on the eye color and exact image matching to the training images. Its takes more time to get result and low quality images has some noise and blur content under the different lighting conditions these can not converted to high pixels images . In proposed system we using KNN-based image processing technique to detect weather an eye is drugged or not. In proposed methodology accepts both low and high quality images and it takes few seconds to get result. After the image preprocessing the images are converted into binary and kept in a Color model (RGB).

A. Image Acquisition

Sample photos are gathered in this phase in order to refine the classifier algorithm and create the classifier model. Healthy and affected eye images were taken by using mobile phone or digital camera and utilized to put the classification algorithm through examination and instruction. Images were taken in different angles, under the different environmental and lighting conditions. The standard JPG format was used to store these images.

B. Image Preprocessing

Image pre processing involves in enhances the quality of the image. Then all the original eye images were stored in a folders and applying various modifications. Performing specific tasks like image resizing ,noise

reduction and thresholding. Noise reduction is a common task in digital image processing, where you try to remove unwanted or random variations in pixel values from an image.

C. Feature Extraction

Feature extraction is performed to highlight the distinctive characteristics of the sclera affected by drug use. This study employs the Local Binary Pattern (LBP) technique due to its effectiveness in texture classification. LBP captures the texture patterns by comparing each pixel with its neighboring pixels, encoding these relationships into binary patterns. Local Binary Pattern (LBP): For each pixel in the image, the algorithm compares it with its neighbors and assigns a binary value. The resulting binary pattern for each pixel forms a texture descriptor for the entire image.

D. Image Segmentation

All preprocessed images were converted into color models and kept one in the original way (RGB). Because the identifying suitable color model for preprocessing is one of the outcomes of this research. After that, the image was converted to binary format. This format values were clustered using the KNN algorithm.

E. Binary Conversion

Transforming the preprocessed images into a binary format where the sclera and non-sclera regions are distinctly identified.

F. Applying Training Set

The segmented output, constructed through feature extraction, is now complete. After segmenting images to isolate eye features. The training set involves marking these segmented areas as "Normal" or "Drugged" eyes. These marked images are used to teach computer models to recognize and distinguish between normal and drugged eyes. The goal is to train these models to accurately identify drugged eye patterns for detection purposes.

G. KNN Classification

The core of the proposed method is the KNN classifier. The steps involved are: Training Phase: The model is trained with labeled images, where the sclera region is marked as either "Normal" or "Drugged." Distance Calculation: For each test image, the Euclidean distance between the test image features and the training image features is calculated. K-Nearest Neighbors Identification: The K closest training images to the test image are identified based on the calculated distances. Majority Voting: The class of the test image is determined by the majority class among its K-nearest neighbors.

H. Experimental Results

In this phase the algorithm itself comparing the graph of the trained dataset with the graph of the input image. Based on the comparison of the input graph and the training data set graph KNN concludes the result which is drugged or note.

IV. EXPERIMENTAL RESULTS AND FINDINGS

Sl. No.	Reddish Section Count	Output	Status Of Eye
1	32	0	Not Drugged
2	19	1	Drugged
3	24	1	Drugged
4	27	1	Drugged
5	13	0	Not Drugged

Two base folders were utilized to identify drugged eyes based on their accuracy after the training set photographs were applied. The dataset for two classes refers to these files.

To boost model accuracy, the rows of training files were randomly switched during training and testing. To ensure accuracy, each training file underwent five rounds of testing and verification. The dataset identified two categories, and accuracy is notably high for non-drugged eyes, which improves the overall drugged eye detection values. The system delivers precise results within seconds, maintaining high accuracy for both low and high pixel images.

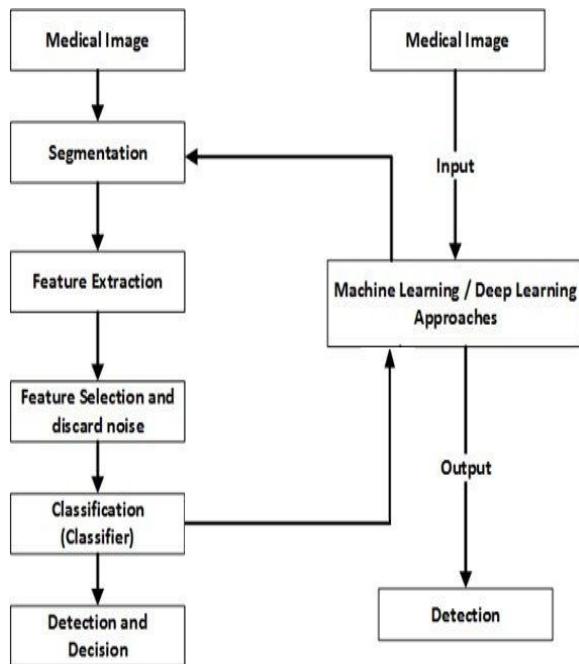


Fig 3.1 Block Diagram of Methodology



Fig 4.1 Drugged Sample 1



Fig 4.2 Drugged Sample 2

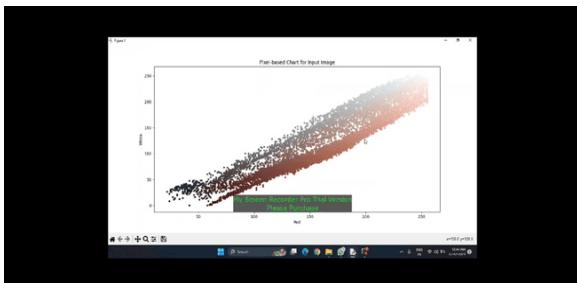


Fig 4.3 Pixel based chart for Not Drugged



Fig 4.4 Histogram graph for Not Drugged

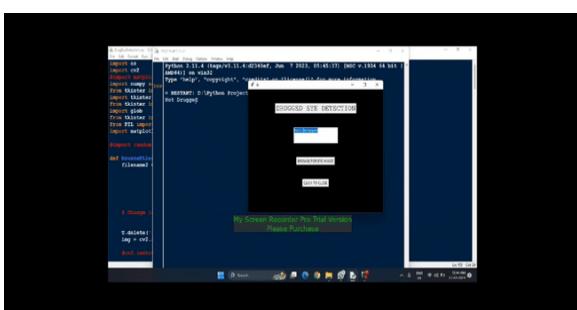


Fig 4.5 Result

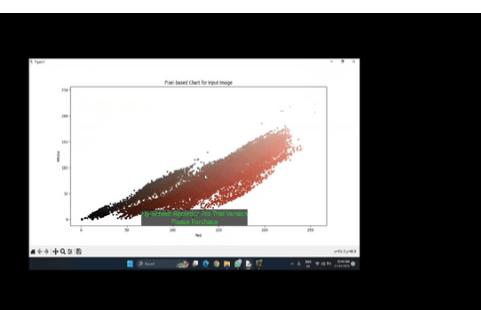


Fig 4.6 Pixel based chart for Drugged

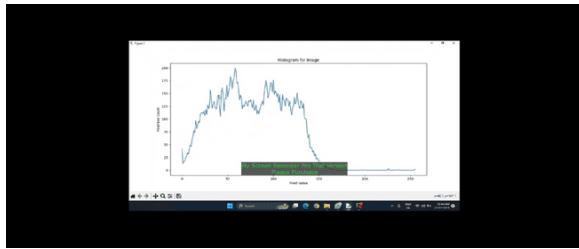


Fig 4.7 Histogram graph for Drugged

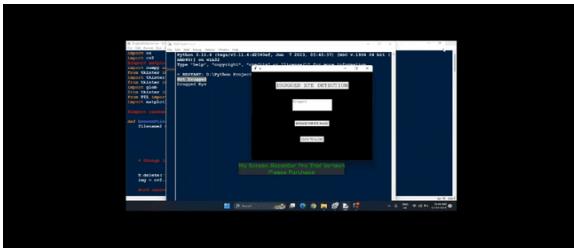


Fig 4.8 Result

V. CONCLUSION

The research proposes and tests an approach using image processing to detect drug use in the eye. We have developed a powerful drugged eye detection system that combines image acquisition, preprocessing, segmentation, and machine learning training. Our findings demonstrate how well the system can recognize patterns in pictures linked to drug impact. Our results highlight how well our system works to identify these patterns, showing how machine learning and image processing may be used to provide accurate and useful drugged eye identification. This project highlights how these technologies can be used to increase the reliability and accuracy of drug use detection by automated picture analysis, providing insightful information about the practical uses of these technologies. This project provides insightful information on the practical uses of integrating machine learning and image processing for accurate drugged eye detection.

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