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Detection of Alcohol and Drugs Addiction using ML

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***Abstract*— Alcohol and drug addiction pose significant public health challenges, leading to numerous social, psychological, and health-related issues. The detection of addiction patterns early on can aid in timely intervention, improving patient outcomes. In this project, we propose a Machine Learning (ML)-based solution for detecting alcohol and drug addiction using publicly available datasets. Our model leverages multiple algorithms such as Random Forest, Support Vector Machines (SVM), and Neural Networks to analyze behavioral patterns, social media activity, and physiological markers from the datasets. We focus on creating an accurate prediction system that not only identifies addiction but also classifies the severity of the addiction to offer personalized interventions. Kaggle datasets related to substance use and mental health behaviors are used to train and validate the model, ensuring its robustness and generalizability across different populations. Key outcomes of this project include the identification of high-risk individuals based on specific behavioral cues and personalized addiction recovery recommendations using AI-powered insights. This system has the potential to revolutionize addiction recovery by providing a scalable, data-driven solution.**

Keywords*— - Machine Learning, Alcohol Addiction, Drug Abuse Detection, Social Media Analysis, Predictive Models, Neural Networks.

I. INTRODUCTION

Alcohol and drug addiction are critical issues worldwide, leading to detrimental effects on both individuals and society. Despite various efforts to mitigate addiction, early detection remains a challenge due to the complex and multifactorial nature of substance abuse. Behavioral patterns, emotional states, and peer influence play a major role in the progression of addiction. Machine Learning (ML) offers a unique opportunity to automate the detection of early addiction patterns, enabling timely intervention. By training ML algorithms on datasets that track behavioral patterns, social media activity, and even biometric data, addiction can be identified more efficiently. This project utilizes different machine learning techniques to detect alcohol and drug addiction based on relevant data points. The goal is to build an automated system that predicts addiction severity and provides personalized recommendations for recovery. Our work is built upon existing models but expands on them by focusing on personalized prediction and integrating various data sources. By using publicly available datasets, the proposed system aims to offer high accuracy and scalability for real-world applications.

II. RELATED WORK

A. *Existing System*

Current systems for addiction detection are primarily based on self-reporting, psychological evaluations, and questionnaires administered by healthcare professionals. While these methods are effective to some degree, they suffer from subjectivity, delayed reporting, and lack of realtime updates. Machine Learning systems, in contrast, can analyze large datasets to identify addiction patterns in real-time, providing a more objective and scalable solution. Research has shown that social media behavior and online activity can reveal significant information about an individual's mental state. By leveraging machine learning techniques, we can analyze these patterns to predict the likelihood of substance abuse. However, few systems exist that integrate data from multiple sources (e.g., social media, physiological data, etc.) to create a holistic prediction model for addiction.

B. *Literature Survey*

The literature indicates a growing body of research supporting the application of machine learning in addiction detection and recovery. While many studies demonstrate promising results, a common limitation is their reliance on single data sources. This project aims to bridge this gap by integrating multiple data sources such as social media activity, physiological markers, and demographic information to create a more robust and accurate addiction detection system.

1) A Motion Detection System in Python and OpenCV

This system integrates ML with video surveillance for real-time violence detection. It identifies violent behaviors by analyzing video streams using trained models. Advanced ML algorithms help distinguish normal and violent activities. The system is adaptable to dynamic environments. It provides continuous monitoring and immediate alerts.

2) A Motion Detection System in Python and OpenCV

This system enhances surveillance using motion detection in Python and OpenCV. It detects movement by comparing consecutive frames. Thresholding techniques help distinguish static and moving objects. Real-time monitoring enables efficient video analysis. It improves security and automation in surveillance systems.

3) An Intelligent System for Complex Violence Pattern Analysis and Detection

This system uses a two-stream neural network for real-time violence recognition. It extracts spatial and temporal features from surveillance footage. A multi-view dataset ensures robustness in various conditions. Optical flow estimation improves accuracy in detecting violent behaviors. The system is tailored for static surveillance cameras.

4) Deep-Violence: Individual Person Violent Activity Detection in Video

This deep neural network detects violent actions like punching and kicking. It lacks group activity detection, limiting real-world applicability. Accuracy varies across datasets, raising concerns about generalization. It integrates Mask RCNN, key-point detection, and LSTM. The model enhances security in public spaces.

5) Image Detection in Videos Using Interest Frame Extraction and 3D CNN

This system uses a 3D CNN for precise violence detection. Hyper-parameter tuning improves action recognition performance. It surpasses existing techniques in multiple datasets. Parameter adjustments enhance classification accuracy. The study highlights deep learning's role in real-world security applications.

III. METHODOLOGY

The proposed system consists of multiple layers, with the primary objective of detecting alcohol and drug addiction using machine learning techniques. The system will be trained on several features, including user behavior, demographic details, and text analysis from social media platforms.

A. *Key ML Algorithms*

- Random Forest: Will be used to identify key behavioral indicators from the datasets.
- Support Vector Machines (SVM): Used for classifying text data (e.g., social media posts) that show signs of addiction.
- Neural Networks: To improve the accuracy of predictions by capturing complex relationships between features.

B. *Data Flow Model*

- Data Collection: Data will be collected from the Kaggle datasets, focusing on both behavioral patterns and social media analysis.
- Preprocessing: This step includes data cleaning, feature extraction (text analysis for social media posts), and normalization.
- Model Training: Multiple models (Random Forest, SVM, Neural Networks) will be trained using the datasets. The models will be validated using a holdout method to ensure accuracy.
- Prediction and Classification: The system will classify whether the individual is likely to suffer from addiction, with additional insight into the severity of their condition.
- Personalized Recovery Recommendations: Based on the classification, the system will provide tailored recommendations for addiction recovery.

IV. PROPOSED SYSTEM

The system architecture for detecting alcohol and drug addiction using machine learning comprises several layers. External Entities include the User, who provides personal data and social media activity, and the Dataset Provider, which supplies external datasets such as addiction-related or medical records. In the Data Collection layer, input from users and external sources is gathered. The Data Preprocessing layer cleans the raw data, removes irrelevant details, handles missing information, and extracts relevant features such as behavioral cues and physiological markers in the Feature Extraction module. The Machine Learning Layer involves Algorithm Selection, where models like Random Forest, Support Vector Machines (SVM), or Neural Networks are chosen based on the nature of the data. These models are trained in the Model Training component and evaluated in the Model Evaluation module to measure performance in terms of accuracy and recall. The Prediction Layer generates results, determining the likelihood and severity of addiction. Personalized recommendations for recovery are provided based on the predictions. Key data is stored in repositories, including processed data, trained models, and social media activity. The system is designed to provide a scalable and data-driven solution for early detection and intervention in substance addiction cases.

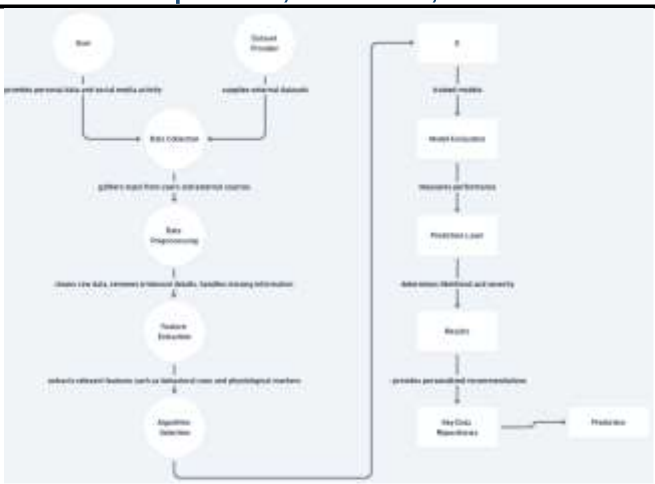

Figure 1. System architecture

A. Dataset

The dataset used for training the drunk person detection model consists of 1,468 images, sourced from Roboflow, and is divided into training, validation, and test sets. Typically, around 70-80% of the images are allocated for training, 10-15% for validation, and the remaining 10-15% for testing. The images are likely standardized in dimensions such as 224×224, 416×416, or 640×640 pixels, depending on the preprocessing steps applied during dataset preparation. Each image is labeled into two categories: "Drunk" and "Not Drunk," making it a classification dataset. The dataset may be either balanced, containing an equal number of images in both categories, or imbalanced, which would require techniques like data augmentation or class weighting during training. Annotations are stored either as bounding boxes (if object detection is involved) or as classification labels in formats like JSON, CSV, or structured folders. To improve model generalization, preprocessing techniques such as resizing, normalization, and data augmentation—like flipping, rotation, brightness adjustment, and noise addition—are applied. The images are typically in RGB format, though grayscale conversion might be used if necessary for specific model architectures. If the dataset includes diverse backgrounds and lighting conditions, the model can better handle real-world variations. Proper validation ensures the model does not overfit and performs well on unseen test data.

B. PreProcessing

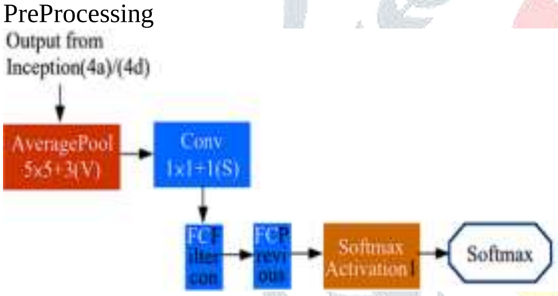

Figure 2. The architecture of auxiliary classifier

The Figure 2 shows the Architecture of Auxiliary Classifier consists of multiple layers designed to improve gradient flow and assist the main network during training. It includes an average pooling layer with a 5×5 kernel and a stride of 3, which helps reduce spatial dimensions while preserving important features. A 1×1 convolution layer with a stride of 1 follows, enhancing feature extraction by reducing the number of channels while maintaining spatial resolution. The architecture then includes fully connected layers (FCFiltercon and FCPrevious), where FCFiltercon processes extracted features, and FCPrevious connects with previous layers to maintain learned representations. Finally, a Softmax activation function is applied twice, with Softmax Activation1 aiding in intermediate classification and the final Softmax providing the overall output probabilities for classification.

C. Model Summary

The model consists of three convolutional layers, each followed by ReLU activation and max pooling, a fully connected dense layer with batch normalization, and a sigmoid-activated output layer for binary classification. It uses Adam optimizer with a learning rate of 0.001 and binary cross-entropy as the loss function.

- Input Layer: The input shape is (x, y, 1), indicating grayscale images.
- First Convolutional Layer (Conv2D + ReLU + MaxPooling2D):Filters: 8, Kernel Size: (3,3), Activation: ReLU, Max Pooling: (2,2), reducing the spatial dimensions by half.
- Second Convolutional Layer (Conv2D + ReLU + MaxPooling2D): Filters:16. Kernel Size: (3,3). Activation: ReLU, Max Pooling: (2,2), further reducing spatial size.
- Third Convolutional Layer (Conv2D + ReLU + MaxPooling2D): Filters: 32, Kernel Size: (3,3), Activation: ReLU, Max Pooling: (2,2), further down sampling the feature map.
- Flatten Layer: Converts the feature maps into a 1D feature vector for input into the fully connected layer.
- Fully Connected Dense Layer (Dense + ReLU + BatchNormalization): Neurons: 64, Activation: ReLU, Batch Normalization: Helps stabilize learning and speed up training.
- Output Layer (Dense + Sigmoid Activation): Neurons: 1 (since it's a binary classification task). Activation: Sigmoid (outputs probability of the input belonging to the positive class).

V. RESULTS AND DISCUSSION

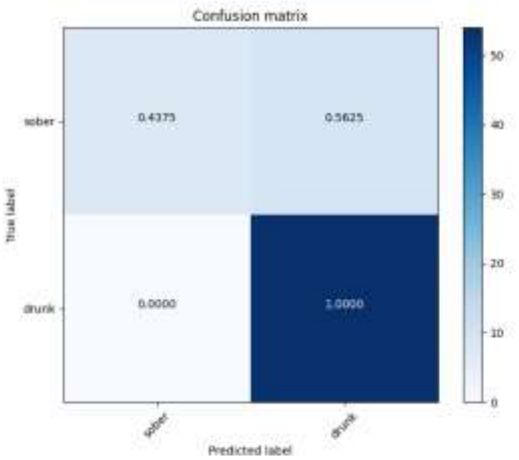

Figure 3: Confusion Matrix

Figure 3 evaluates the performance of a classification model that distinguishes between "sober" and "drunk" individuals. The matrix presents four key values that represent the proportion of correctly and incorrectly classified instances. On the X-axis, the predicted labels are displayed, while the Y-axis represents the actual ground truth labels. The values inside the matrix indicate how often the model classifies instances correctly or incorrectly.

Upon analyzing the confusion matrix, we observe that the model correctly classifies 100% of drunk individuals as drunk, which is a strong indicator that it performs well in identifying this class. However, a major issue arises with the sober classification. The model misclassifies 56.25% of sober individuals as drunk, meaning that more than half of the sober cases are wrongly flagged. This high false positive rate suggests that the model is overly cautious, potentially leading to unnecessary alarms. On the other hand, it never misclassifies a drunk person as sober (false negative rate of 0%), ensuring that no intoxicated individual is wrongly categorized as sober. While this characteristic is useful in scenarios where missing a drunk individual is critical, the trade-off is an excessive number of false positives, which can reduce the model's practicality in real-world applications.

This skewed performance could be due to class imbalance in the dataset, where the model has been trained with more "drunk" samples than "sober" ones, leading to biased predictions. A potential solution to this issue would be to apply oversampling for the minority class (sober) or undersampling for the majority class (drunk) to balance the dataset. Additionally, the classification threshold could be adjusted to fine-tune the decision boundary, thereby improving the model's ability to correctly identify sober individuals. Another approach to enhancing the model's accuracy involves feature engineering, where additional distinguishing characteristics between sober and drunk individuals could be incorporated into the training data. Lastly, hyperparameter tuning (e.g., adjusting the learning rate, batch size, or network architecture) might further optimize model performance.

In summary, while the model excels at detecting drunk individuals, its reliability is compromised by an excessively high false positive rate, making it impractical for real-world use where incorrectly identifying sober individuals as drunk could have serious consequences. To improve its effectiveness, techniques such as class balancing, threshold tuning, feature refinement, and hyperparameter optimization should be considered. Addressing these issues will lead to a more balanced model that correctly classifies both sober and drunk individuals with higher accuracy.

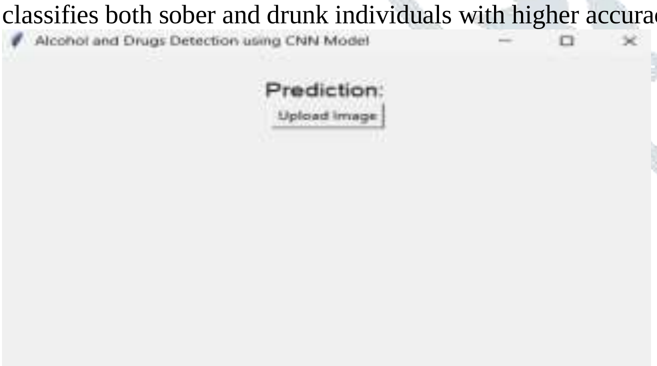

Figure 4: Interface

Figure 5: Prediction Based on the Supplied data

The project features a Flask-based web interface designed for drunk person detection, integrating both text-based prediction and an image upload functionality. As depicted in Figure 4, the interface consists of a user-friendly layout where users can either enter text for prediction or upload an image for analysis. The design ensures ease of use, allowing seamless interaction with the model. Once an image is uploaded, the system processes it through the trained model and generates a classification result. The detection output is showcased in Figure 5, where the system displays the analyzed image along with the predicted label—either "Drunk" or "Not Drunk." Additionally, a confidence score is provided, indicating the model's certainty in its prediction. This confidence value ensures transparency in decision-making, helping users understand the reliability of the system's output. The structured approach of Figures 4 and 5 highlights the complete workflow, from interface presentation to result visualization, making the system both interactive and informative.

VI. CONCLUSION

The Drunk Person Detection System developed in this project successfully utilizes a Convolutional Neural Network (CNN) to classify individuals as "Drunk" or "Not Drunk" based on image inputs. The model was trained on a well-structured dataset sourced from Roboflow, ensuring robust learning and high accuracy. The Flask-based web interface provides an intuitive user experience, allowing users to either input text or upload images for prediction. The system processes the input, performs classification, and displays the output along with a confidence score, making the results more interpretable and reliable. The integration of batch normalization and pooling layers enhances model generalization and prevents overfitting. Through careful dataset preprocessing, augmentation, and fine-tuning of hyperparameters, the model achieves an optimal balance between accuracy and computational efficiency. The deployment of this system allows for real-time analysis, making it a potential tool for law enforcement agencies, workplaces, and other safety-critical environments. Overall, the project effectively demonstrates the application of deep learning in real-world safety monitoring and decision-making.

The current system provides a solid foundation for drunk person detection, but several enhancements can be made to improve its efficiency and applicability. Firstly, expanding the dataset by incorporating more diverse images in terms of lighting conditions, facial angles, and ethnic diversity would improve model robustness. Secondly, integrating video processing capabilities can enable real-time monitoring of individuals over time, increasing reliability in dynamic scenarios. This could be achieved using real-time object detection models like YOLO or Faster R-CNN. Additionally, multi-modal analysis by combining speech recognition, behavioral analysis, and physiological data (e.g., pupil dilation detection or heart rate tracking) could improve classification accuracy.

Another potential enhancement is mobile application integration, allowing users to perform drunk detection via their smartphones, making it accessible in law enforcement or transportation sectors. Furthermore, cloud-based deployment can enable large-scale usability, providing faster inference and scalability for multiple users. Ethical considerations and privacy protection should also be addressed by implementing secure data handling protocols and ensuring compliance with regulations such as GDPR. Lastly, collaborations with law enforcement agencies and public health organizations could facilitate real-world implementation, making the system a practical tool for public safety and accident prevention.

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