ML Framework for Efficient Assessment and Prediction of Human Performance in Collaborative Learning Environments

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ABSTARCT

Collaborative learning methods have been implemented broadly by organizations at all stages, as research recommends that active human involvement in cohesive and micro group communications is critical for effective learning. In current research, an important line of inquiry focuses on finding accurate evidence and valid assessment of these micro-level interactions which supports collaborative learning. Even though there is a long practice of using mathematical models for modeling human behavior, Cipresso (2015) introduced a computational psychometrics-based method for modeling characteristics of real behavior. Cipresso's article provides us with a way to extract dynamic interaction features from multimodal data for modeling and analyzing actual situations. The objective of this work is to propose a machine learning-based methodology system architecture and algorithms to find patterns of learning, interaction, and relationship and effective assessment for a complex system involving massive data that could be obtained from a proposed collaborative learning environment (CLE). Collaborative learning may take place between dyads or larger team members to find solutions for real time events or problems, and to discuss concepts or interactions during situational judgment tasks (SJT). Modeling a collaborative, networked system that involves multimodal data presents many challenges. This paper focuses on proposing a Machine Learning - (ML)-based system architecture to promote understanding of the behaviors, group dynamics, and interactions in the CLE. Our framework integrates techniques from computational psychometrics (CP) and deep learning models that include the utilization of convolutional neural networks (CNNs) for feature extraction, skill identification, and pattern recognition. Our framework also identifies the behavioural components at a micro level and can help us model behaviors of a group involved in learning.

Keywords: collaborative learning environment, machine learning, behaviour analysis, deep learning.

1. INTRODUCTION

Collaborative learning methods have been implemented broadly by organizations at all stages, as research recommends that active human involvement in cohesive and micro group communications is critical for effective learning [1]. In current research, an important line of inquiry focuses on finding accurate evidence and valid assessment of these micro-level interactions which supports collaborative learning. In this paper, we propose a three-stage method to explore and study collaborative group behaviors. The first stage integrates, and processes multimodal data obtained in a collaborative learning environment (CLE) that includes sensor input, audio, video, eye tracking, facial expressions, movement, posture, gestures, and behavioural interaction log data. The second stage performs feature extraction and cloud computation using computational psychometrics (CP) and convolutional neural network (CNN)-based deep learning for skill, pattern, and trend identification. Finally, the third stage uses the parameters measured in the previous two stages to understand and model group interactions, competencies, and collaborative behavior at a micro-level. The third stage uses machine learning for effective assessment and visualization of group dynamics such as correctly assessing the increase in the groups' level of shared understanding of different perspectives, and ability to clarify misconceptions.

2. LITERATURE SURVEY

Chopade et al. focused on proposing a Machine Learning - (ML)-based system architecture to promote understanding of the behaviors, group dynamics, and interactions in the CLE. This framework integrated techniques from computational psychometrics (CP) and deep learning models that include the utilization of convolutional neural networks (CNNs) for feature extraction, skill identification, and pattern recognition. This framework also identified the behavioural components at a micro level and can help us model behaviors of a group involved in learning.

Zhang et al. proposed a prediction-based human-robot collaboration model for assembly scenarios. An embedded learning from demonstration technique enables the robot to understand various task descriptions and customized working preferences. A state-enhanced convolutional long short-term memory (ConvLSTM)-based framework is formulated for extracting the high-level spatiotemporal features from the shared workspace and predicting the future actions to facilitate the fluent task transition. This model allows the robot to adapt itself to predicted human actions and enables proactive assistance during collaboration. We applied our model to the seats assembly experiment for a scale model vehicle and it can obtain a human worker's intentions, predict a co-worker's future actions, and provide assembly parts correspondingly. It has been verified that the proposed framework yields higher smoothness and shorter idle times, and meets more working styles, compared to the state-of-the-art methods without prediction awareness.

Tang et al. investigated and compared the cycle time, waiting time, and operators' subjective preference of a human–robot collaborative assembly task when three handover prediction models were applied: traditional method-time measurement (MTM), Kalman filter, and trigger sensor approaches. The Kalman filter prediction model could adjust the handover timing according to the operator's current speed and reduce the waiting time of the robot and operator, thereby improving the subjective preference of the operator. Moreover, the trigger sensor method's inherent flexibility concerning random single interruptions on the operator's side earned it the highest scores in the satisfaction assessment.

Bianchi et al. presented an innovative HAR system, exploiting the potential of wearable devices integrated with the skills of deep learning techniques, with the aim of recognizing the most common daily activities of a person at home. The designed wearable sensor embeded an inertial measurement unit (IMU) and a Wi-Fi section to send data on a cloud service and to allow direct connection to the Internet through a common home router so that the user themselves could manage the installation procedure. The system is conceived for daily activity monitor and nine different activities can be highlighted with an accuracy of 97%.

Wan et al. designed a smartphone inertial accelerometer-based architecture for HAR. When the participants perform typical daily activities, the smartphone collects the sensory data sequence, extracts the high-efficiency features from the original data, and then obtains the user's physical behavior data through multiple three-axis accelerometers. The data are pre-processed by denoising, normalization and segmentation to extract valuable feature vectors. In addition, a real-time human activity classification method based on a convolutional neural network (CNN) is proposed, which uses a CNN for local feature extraction. Finally, CNN, LSTM, BLSTM, MLP and SVM models are utilized on the UCI and Pamap2 datasets.

Nwekw et al. focused to provide in-depth summaries of deep learning methods for mobile and wearable sensor-based human activity recognition. The review presented the methods, uniqueness, advantages, and their limitations. This framework not only categorise the studies into generative, discriminative and hybrid methods but also highlight their important advantages. Furthermore, the review presented classification and evaluation procedures and discusses publicly available datasets for mobile sensor human activity recognition. Finally, this work outlined and explained some challenges to open research problems that require further research and improvements.

Hassan et al. presented a smartphone inertial sensors-based approach for human activity recognition. Efficient features are first extracted from raw data. The features include mean, median, autoregressive coefficients, etc. The features are further processed by a kernel principal component analysis (KPCA) and linear discriminant analysis (LDA) to make them more robust. Finally, the features are trained with a Deep Belief Network (DBN) for successful activity recognition. The proposed approach was compared with traditional expression recognition approaches such as typical multiclass Support Vector Machine (SVM) and Artificial Neural Network (ANN) where it outperformed them.

Zhou et al. developed an intelligent autolabeling scheme based on deep Q-network (DQN) with a newly designed distance-based reward rule which can improve the learning efficiency in IoT environments. A multisensory based data fusion mechanism is then developed to seamlessly integrate the on-body sensor data, context sensor data, and personal profile data together, and a long short-term memory (LSTM)-based classification method is proposed to identify fine-grained patterns according to the high-level features contextually extracted from the sequential motion data.

Chen et al. proposed a new deep learning-based approach, i.e., attention based bi-directional long short-term memory (ABLSTM), for passive human activity recognition using WiFi CSI signals. The BLSTM is employed to learn representative features in two directions from raw sequential CSI measurements. Since the learned features may have different contributions for final activity recognition, this framework leveraged on an attention mechanism to assign different weights for all the learned features.

Xu et al. proposed a deep learning model (InnoHAR) based on the combination of inception neural network and recurrent neural network. The model inputs the waveform data of multi-channel sensors end-to-end. Multi-dimensional features are extracted by inception-like modules by using various kernel-based convolution layers. Combined with GRU, modeling for time series features is realized, making full use of data characteristics to complete classification tasks. Through experimental verification on three most widely used public HAR datasets, this proposed method showed consistent superior performance and has good generalization performance, when compared with the state-of-the-art.

Kong et al. surveyed the complete state-of-the-art techniques in action recognition and prediction. Existing models, popular algorithms, technical difficulties, popular action databases, evaluation protocols, and promising future directions are also provided with systematic discussions.

3. EXISTING SYSTEM

ML falls under the larger canvas of Artificial Intelligence. ML seeks to build intelligent systems or machines that can automatically learn and train themselves through experience, without being explicitly programmed or requiring any human intervention. In this sense, ML is a continuously evolving activity. It aims to understand the data structure of the dataset at hand and accommodate the data into ML models that can be used by companies and organizations. Following are the benefits of ML.

- Enhanced decision-making: ML uses advanced algorithms to improve the decision-making process capacity. It facilitates innovative models and business services simultaneously. It provides a deep understanding of the variations and types of data patterns. You can determine which step to take next based on the variations and data patterns.
- Increases business productivity: It improves the business process and productivity, contributing to business growth. It helps you to adapt to the changing situations at workplaces quickly. The data continue to be updated daily. So, the work environment, too, keeps on changing quickly. ML reduces the chances of error occurrence by half. Hence, it boosts business productivity. This aspect is important to consider when carrying out deep learning vs neural network.
- Removes manual data entry: One of the most common concerns in many organizations is the usage of duplicate records. ML algorithms use predictive models that significantly avoid any errors caused by manual data entry. The corresponding programs use the discovered data to enhance these processes. Hence, the employees can save time to focus on other important business tasks.
- Guarantees customer satisfaction: The ML algorithms are uniquely designed to continue attaining experience with time. They are accurate and efficient. These algorithms improve the machines' decision-making skills. ML can anyhow find a way to make accurate decisions or predictions, although the data is overwhelming and ever-increasing. It benefits businesses with the latest market opportunities related to revenue. As a result, it can satisfy the customers' expectations and boost your business' sales in less time. Moreover, it can quickly recognize threats in the market. You can compare deep learning vs neural networks based on this aspect to have a clear judgment.
- Provides product recommendation: Unsupervised research assists in the development of suggestion systems depending on goods. Currently, most e-commerce platforms use ML to provide product recommendations. ML algorithms use the consumers' purchasing experience to balance it with the assets' huge inventory. This helps in detecting secret trends and connects identical products. Finally, these goods are recommended to the consumers.
- Detects spam: ML is widely used for spam detection. It uses spam filters to identify spam and phishing communications.
- Improves network security: ML improves an organization's security. It helps organizations to develop new systems capable of quickly and efficiently recognizing unknown threats. It can track abnormalities present in network activity and automatically execute relevant actions. When the ML algorithm is used for self-training, it removes manual research and analysis. So, it enhances the organization's network security. Many deep learning neural networks are also used for this purpose.
- Simplifies business analysis: ML is used in business analysis that involves huge volumes of precise and quantitative historical data. It is widely used for algorithmic trading, portfolio management, fraud detection, and lending in finance. The future ML applications for finance will entail Chatbots and a few other interfaces for improving customer service, security, and sentiment analysis. Many neural networks and deep learning algorithms are also used to streamline finance analysis.

3.1 Disadvantages

- ML Model makes decisions based on what it has learnt from the data. As a result, while ML models may learn from data, they may need some human interaction in the early stages.
- Moreover, its performance is poor with large dataset.

4. PROPOSED SYSTEM

This application has three modules:

1) Data Collection: collecting data from various sources such as Audio data or video data or sensor data etc.
2) Data Extraction: from collected data features will be extracted and this extracted feature will be analysed by CNN algorithm.
3) Behaviour Prediction: CNN will analyse features obtained from above two modules and then predict behaviour or performance.

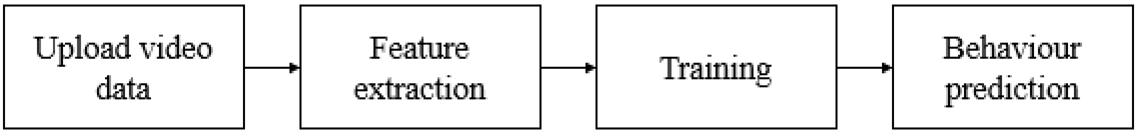


Fig. 1: Block diagram of proposed system.

4.1 Pre-processing

Data pre-processing is a process of preparing the raw data and making it suitable for a machine learning model. It is the first and crucial step while creating a machine learning model.

When creating a project, it is not always a case that we come across the clean and formatted data. And while doing any operation with data, it is mandatory to clean it and put in a formatted way. So, for this, we use data pre-processing task.

4.2 DL-CNN

According to the facts, training and testing of CNN involves in allowing every source data via a succession of convolution layers by a kernel or filter, rectified linear unit (ReLU), max pooling, fully connected layer and utilize SoftMax layer with classification layer to categorize the objects with probabilistic values ranging from.

Convolution layer is the primary layer to extract the features from a source image and maintains the relationship between pixels by learning the features of image by employing tiny blocks of source data. It’s a mathematical function which considers two inputs like source image $I(x, y, d)$ where x and y denotes the spatial coordinates i.e., number of rows and columns. d is denoted as dimension of an image (here d=3 since the source image is RGB) and a filter or kernel with similar size of input image and can be denoted as $F(k_x, k_y, d)$..

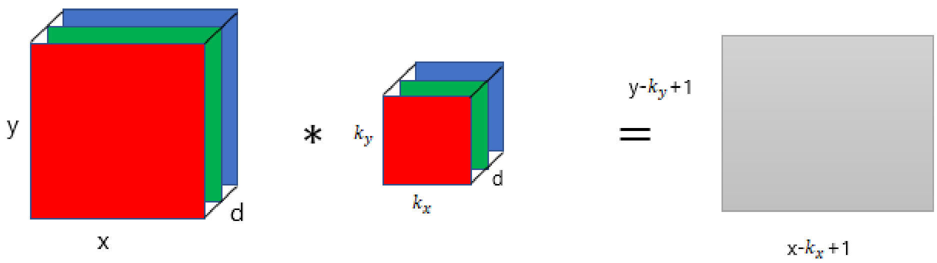
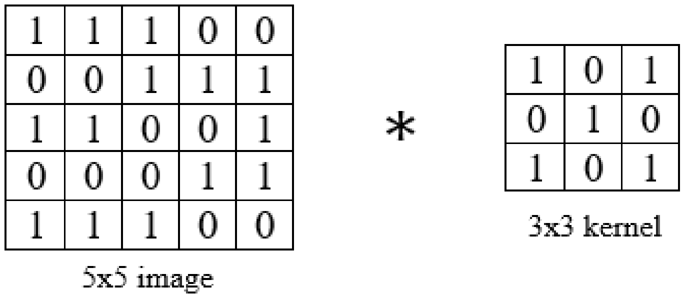
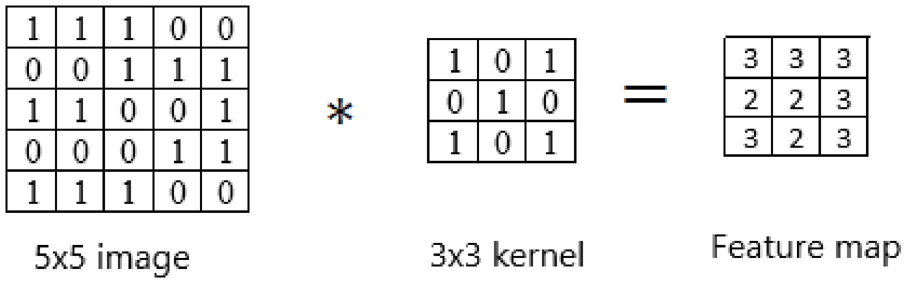


Fig. 2: Representation of convolution layer process.

The output obtained from convolution process of input image and filter has a size of $C\left((x-k_x+1),\left(y-k_y+1\right),1\right)$, which is referred as feature map. Let us assume an input image with a size of 5×5 and the filter having the size of 3×3. The feature map of input image is obtained by multiplying the input image values with the filter values.



(a)



(b)

Fig. 3: Example of convolution layer process (a) an image with size 5×5 is convolving with 3×3 kernel (b) Convolved feature map.

ReLU layer

Networks those utilizes the rectifier operation for the hidden layers are cited as rectified linear unit (ReLU). This ReLU function $\mathcal{G}(\cdot)$ is a simple computation that returns the value given as input directly if the value of input is greater than zero else returns zero. This can be represented as mathematically using the function $max(\cdot)$ over the set of 0 and the input x as follows:

$$\mathcal{G}(x) = \max\{0, x\}$$

Max pooing layer

This layer mitigates the number of parameters when there are larger size images. This can be called as subsampling or down sampling that mitigates the dimensionality of every feature map by preserving the important information. Max pooling considers the maximum element form the rectified feature map.

Advantages of proposed system

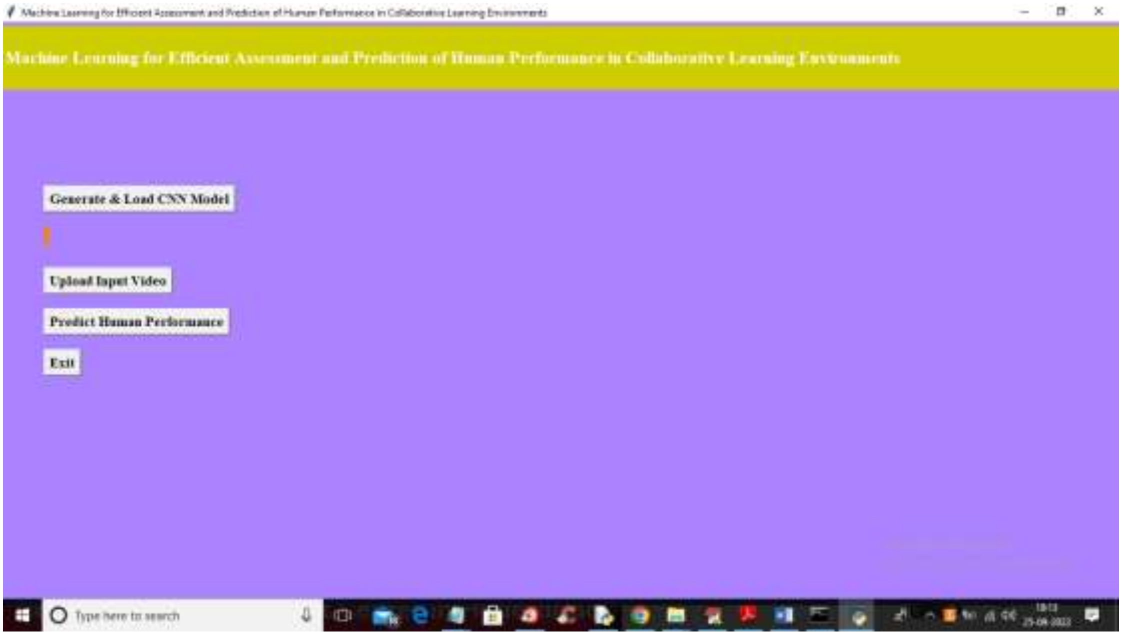
- CNNs do not require human supervision for the task of identifying important features.
- They are very accurate at image recognition and classification.
- Weight sharing is another major advantage of CNNs.

- Convolutional neural networks also minimize computation in comparison with a regular neural network.
- CNNs make use of the same knowledge across all image locations.

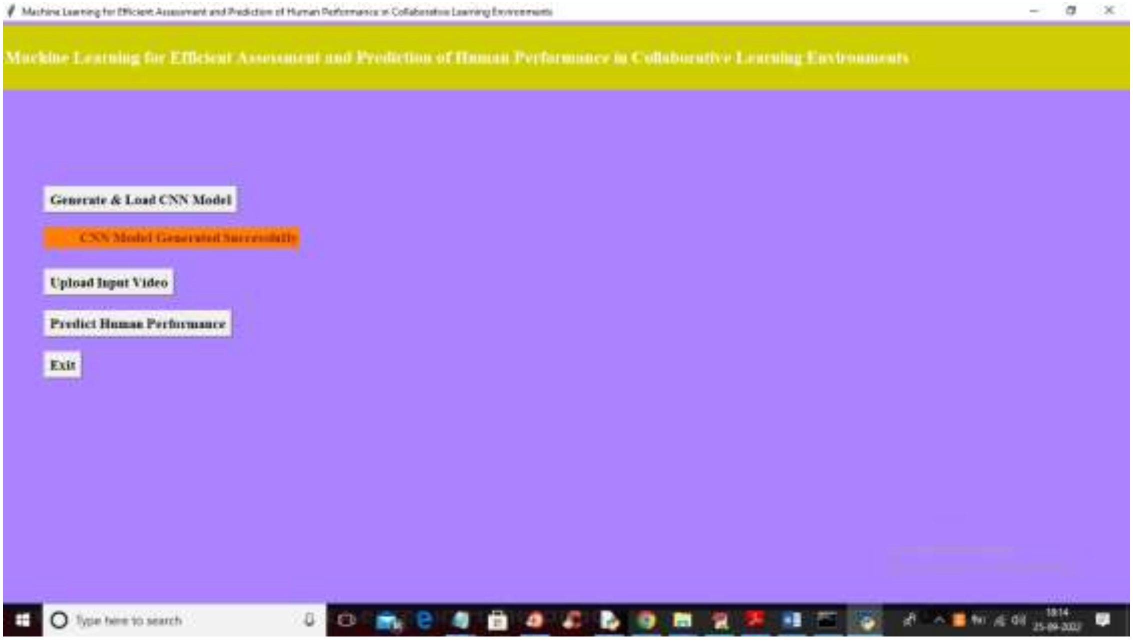
5. RESULTS AND DISCUSSION

This application has three modules:

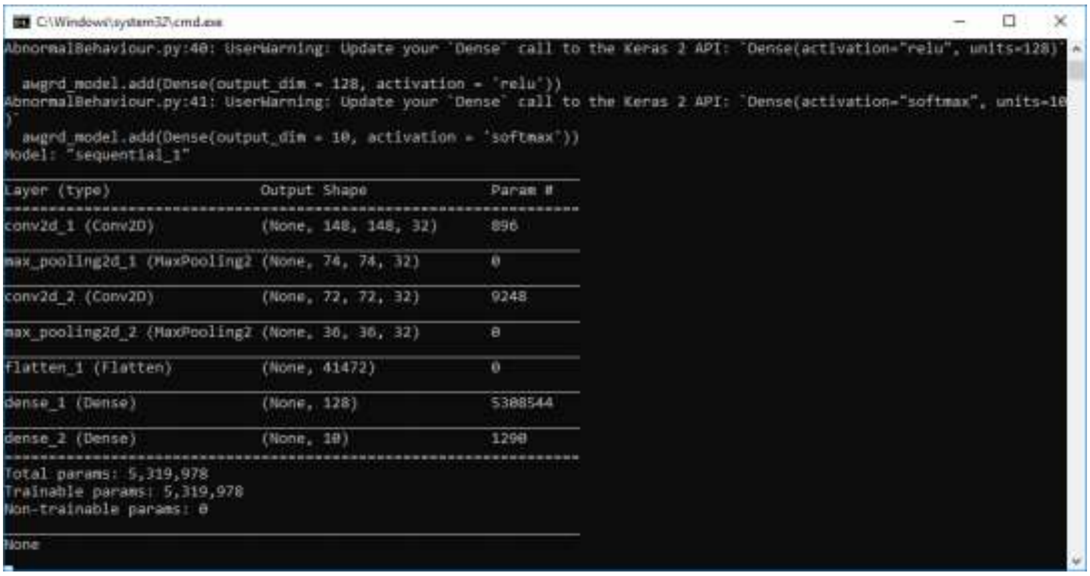
1) Data Collection: collecting data from various sources such as Audio data or video data or sensor data etc.
2) Data Extraction: from collected data features will be extracted and this extracted feature will be analysed by CNN algorithm.
3) Behaviour Prediction: CNN will analyse features obtained from above two modules and then predict behaviour or performance.



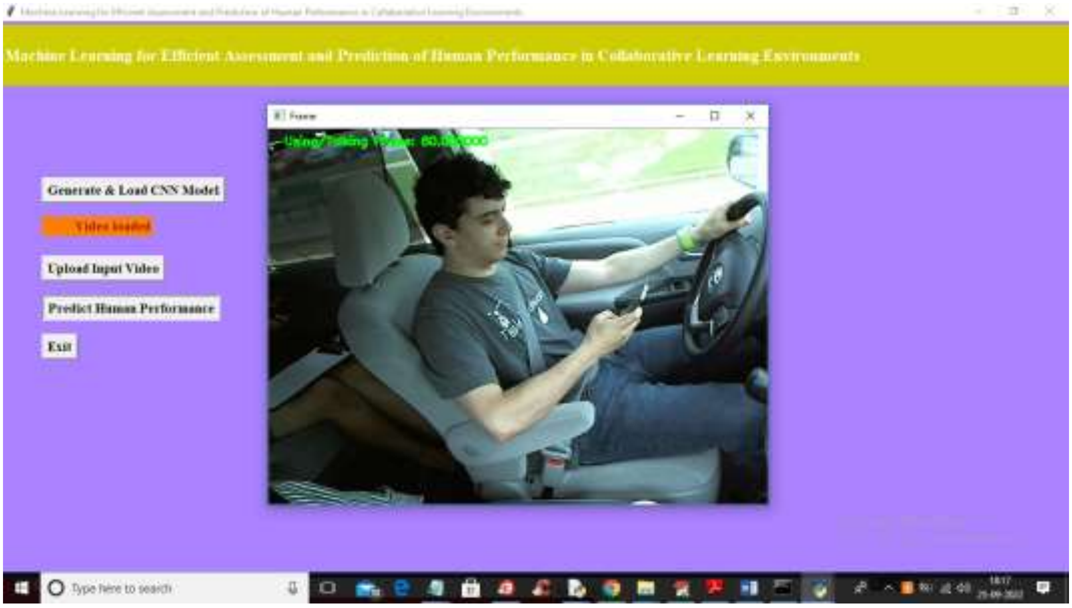
In above screen click on 'Generate & Load CNN Model' button to generate CNN trained model and this model use to predict human performance.



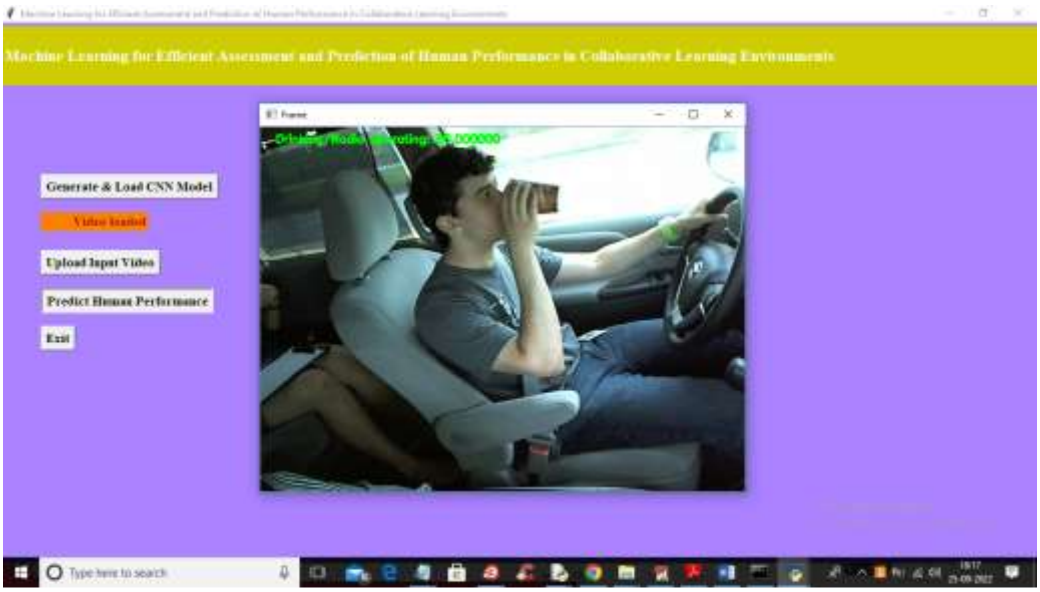
In above screen we can see model is generated and in below screen we can see all details



In above screen we can see CNN model details. Now click on 'Upload Input Video' button to upload video.



In above screen application detected user is using/talking on phone



In above screen we can see user is drinking. Similarly other detection will also be performed.

6. CONCLUSION AND FUTURE WORK

In this paper, we presented feature extraction that may be used during the phase will be implemented for CNN based architecture to identify evidence about teamwork skills from the behavior, group dynamics, and interactions in the CLE. In our future work, we will attempt to build text-based Natural Language Processing (NLP) models to identify or classify various performances.

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