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# Text- Natural Language Processing (NLP)/Machine Learning (ML) Models to Identify or classify various performances of CPS

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# Abstract

This work aims to discover examples of learning, communication, and relationships, and to provide a viable appraisal for a mind-boggling framework that could get enormous information from a proposed collaborative learning environment (CLE). The framework will be based on artificial intelligence (AI). While completing situational judgment tasks (SJT), dyads or larger groups of coworkers may engage in community-oriented learning by discussing potential solutions to problems and sharing ideas. Numerous challenges arise while attempting to demonstrate a coordinated framework that incorporates multimodal data. A Machine Learning (ML) based framework is proposed in this study to enhance understanding of the CLE's procedures, bunch constituents, and linkages. A combination of techniques from computational psychometrics (CP) and deep learning models, our approach makes use of CNNs for feature extraction, expertise distinguishing proof, and example recognition. We may also rely on our system to help us identify the social components at a microscopic level and withdisplaying the rituals of a meeting related to education.Algorithm for convolutional neural networks (CNNs), machine learning, collaborative learning.

# 1. INTRDUCTION

Because studies show that active human participation in powerful and smaller-scale group exchanges is fundamental for effective learning, associations at all levels have made heavy use of synergistic learning strategies [1]. The discovery of exact evidence and valid evaluation of these lower scale level cooperations that support communitarian learning is a major theme in momentum study. Despite the fact that numerical models of human behavior have been around for (2015)provided а while, Cipresso а computational psychometrics-based method for demonstrating characteristics of authentic behavior in [2]. The essay by Cipresso [2] provides provides us with a method to demonstrate and analyze real-world situations by extracting distinct cooperative highlights from multimodal data. In this article, we provide a three-pronged approach to study and think about cooperative collecting methods. Sensor input, audio, video, eye tracking, external appearances, development, posture, movements, and conduct connection log data are all part of

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the multimodal information that the primary arrangement integrates and produces in a collaborative learning environment (CLE). Using computational psychometrics (CP) and convolutional neural network (CNN) based deep learning for ability, example, and pattern distinguishing evidence, the next step executes extraction and cloud calculation. The third and final step makes use of the characteristics calculated in the first two stages to understand and display, at a more localized level, the group's communications, capabilities, and common behavior. Stage three makes use of AI to persuasively evaluate and portray group components, such as successfully measuring the growth in group members' common understanding of different perspectives and ability to explain erroneous decisions

2. Tasks Connected

Human-Agent Evaluation: Collaborative Problem-Solving Interaction and Subskill Scoring [3]One of the 21st-century skills identified as a foundational capability for training and workplace success is collaborative problem solving (CPS). A certain level of competence in psychological and social-enthusiastic aptitudes is required of understudies entering the employment. Using an instructional critical thinking game, this research demonstrates a method for CPS-based performance evaluation and provides a framework for assessing CPS-related strengths and weaknesses. Our method uses K-Means clustering to evaluate and investigate the CPS proof's element space, which was constructed using game log-information. Our findings provide clear member groups with varying degrees of CPS skills, which may aid in center repair efforts.Using a custom-built, user-friendly game named "Circuit Runner," we presented a method to handle distinction confirm and, therefore, rate individuals on CPS aptitudes in this article. We developed CPS\* and IS score proportions for social connection abilities that may be used to calculate customers' CPS overall performance reports. When it comes to training and worker success in the 21st century, the CPS execution file will be a major indicator. We plan to examine CPS\*-acquired groups with IS-based bunches and approve IS ratings for a multi-client scenario in our future work. Classification of Images using Artificial Neural Networks with Deep Convolution [10] We trained a massive, deep convolutional neural network to sort the 1.2 million goal images from the ImageNet LSVRC-2010 competition into 1000 unique categories. Our top-1 and top-5 error rates on the test data were 37.5% and 17.0%, respectively, which is a considerable improvement above the previous class best. The six-hundred-thousand-neurons neural network includes five convolutional layers—some of which are followed by max-pooling layers—and three fully linked layers, culminating in a 1000-way softmax. The system is trained using sixty million parameters. By combining nonsaturating neurons with an extraordinarily efficient GPU implementation of the convolution process, we were able to accelerate training. We used a newly developed regularization approach termed "dropout" that proved to be quite effective in reducing overfitting in the fully connected layers. In the ILSVRC-2012 challenge, we used a variant of this approach and achieved a top-5 test blunder pace of 15.3%, while 26.2% achieved the best passing.Based on our findings, a large, deep CNN can achieve record-breaking performance with only administered learning on a very challenging dataset. Surprisingly, removing even a single convolutional layer ruins our system's display. As an example, removing a single layer from the middle causes detracted around 2% from the system's top presentation. Therefore, the depth is crucial for achieving our results.

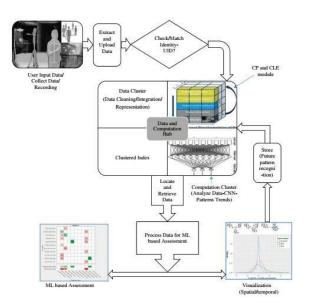
#### 3. The Structure

Our abilities to collect and analyze data in many formats are being transformed by vastly improved, highly adaptable computing. The fields of education, research, and innovation could see fresh developments as a result of this. This could also influence the learning and assessment (LAS) phases. Since information



accelerated processing allows for faster data collection and registration, it alters the way we think about education, research, and innovation [10]. There is much promise for extraordinary uses of information serious versatile registration. The challenge will increase when we need to handle datasets on a massive size, such as Terabyte, Petabyte, or Zettabyte scale. There has been a lot of progress in the perceptual capacities of this data due to recent improvements in processing. Data analysis and interpretation will play a crucial role in validating expected results by accurately spotting data instances and relationships. Representation may have a fundamental role in comprehending the whole picture in understanding linkages within the CLE and in revealing hidden components. Convolutional Neural Networks (CNNs) and DL, a technique within them may require the utilization of an exceptionally proficient Graphical Processing Unit (GPU) usage or for preparing on different GPUs or for uses of this design to generous learning populaces.

In this paper author is describing concept forperson identification using patterns or features extraction obtained from person behaviour, this behaviour data can be obtained from video, audio or user chatting data. To identify person we can make use collaborative learningenvironment (CLE) which consists of data mining algorithms called as machine learning or deep machine learning or computational psychometrics (CP) and convolution neural network (CNN)-based deep learning.



**Figure.1: System Architecture** 

# 1. EXPERIMENTAL RESULTS

Two modules are required to put the aforementioned idea into action, includingThe Data Integration and Processing Module is where we'll be able to compile information for processing from a wide variety of sources, including sensor readings, video and audio recordings, and more. After data collection is complete,



further processing is required to eliminate noise, for example, to eliminate the blurred or static portions of a video or audio file.

It is possible to use a convolutional neural network (CNN) or convolutional neural network (CP) module to extract features from process data; the resulting pattern data may then be used as training data. In the future, this feature data will be used for identification tests in order to make reliable pattern predictions. The CNN algorithm will carry out the pattern matching procedure between the train and test sets. In order to find the closest match for the provided test data, the CNN algorithm will first group all comparable data internally. Your laptop must have audio recording capabilities to capture and store user audio data in order to deploy the Person Identification System utilizing AUDIO data mentioned above. The user will be required to record his voice before proceeding with identification. There are three parts to this application:

Step one: creating an account so you can start recording and saving your voice data.2. User: To utilize this module, the user must first record their voice, and then they must go to the shop to identify all of the sounds.

1. User Identification From File: Instead of recording user can upload voice data from file for identification.

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**Figure.2: Home Screen** 



Figure.3: User Identification



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## Figure.4: Identified User Screen

## [3] EXTENSION

In this project author has given extension or future work in last paragraph of the paper, author is saying if we are implementing CHATBOX then we can analyze chat messages with NLP (Natural Language Processing)techniques to understand chat messages. If we are implementing audio techniques then we needto do more experiments with features extracted using CNN algorithm. So in this paper we have implemented audio techniques so i am doing experiment with CNN features to match similarity or to identify person voice using various techniques such as EUCLIDEAN DISTANCE and COSINE SIMILARITY. Both

this techniques will take users store voice and testing voice and then extract features and then compare both store and testing features to get match percentage. If voice features are close then matching percentage will be closer to 100% else will be closer to 0.



Figure.5:CNNFeatures with Cosine Similarity



#### Conclusion

We presented an ML-based framework designed in this study to extract evidence of cooperation abilities from CLE behavior, bunch components, and messages. We developed a three-tiered robust framework for data-intensive processing and effective evaluation of collaborative CPS abilities.

## REFERENCES

[1] L. Lei, J. Hao, A. von Davier, P. Kyllonen, and J-D. Zapata-Rivera. "A tough nut to crack: Measuring collaborative problem solving." Handbook of Research on Technology Tools for Real-World Skill Development. IGI Global, 2016. 344-359. Web. 28 Aug. 2018.doi:10.4018/978-1-4666-9441-5.ch013

[2] P. Cipresso, "Modeling behavior dynamics using computational psychometrics within virtual worlds," Frontiers in Psychology, vol. 6, no. 1725, p. 22, 6 November 2015. P. Chopade, K. Stoeffler, S. M. Khan, Y. Rosen, S. Swartz, and A. von Davier, "Human- Agent assessment: Interaction and sub-skills scoring for collaborative problem solving," in: Penstein Rosé C. et al. (eds) ArtificialIntelligence in Education. AIED 2018. Lecture Notes in Computer Science, vol 10948, pp 52- 57, June 2018 Springer, Cham, DOIhttps://doi.org/10.1007/978-3-319-93846-2\_10

[3] S. Khan, "Multimodal behavioral analytics in intelligent learning and assessment systems," in Innovative Assessment of Collaboration. Methodology of Educational Measurement and Assessment, A. von Davier, Z. M. and K. P., Eds., Springer, Cham, 2017, pp. 173-184.

[4] S. Polyak, A. von Davier and K.Peterschmidt, "Computational Psychometrics for the measurement of collaborative problem- solving skills," in Proceedings of ACM KDD conference, Halifax, Nova Scotia CANADA, August 2017 (KDD2017), Halifax, Nova Scotia CANADA, 2017.

[5] S. Polyak, A. von Davier, and K. Peterschmidt, "Computational Psychometrics for the measurement of collaborative problem solving skills," Frontiers in Psychology, 8,pp.20-29, 2017. http://doi.org/10.3389/fpsyg.2017.02029

[6] W. Camara, R. O'Connor, K. Mattern, and M.Hanson, "Beyond academics: A Holistic Framework for enhancing education and