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Effective Human Performance Assessment And Prediction Using Machine Learning In Collaborative Learning Environments

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ABSTRACT: In order to find learning, interaction, and relationship patterns as well as the aim like for providing for effective evaluation for a complex system including large amounts of data that may be gathered via a suggested Collaborative Learning Environment (CLE).

When completing Situational Jjudgement Tasks (SJT), dyads or larger groups of team members may work together to acquire new concepts or engage with each other in new ways. There are numerous difficulties in modelling a cooperative, networked system that uses multimodal data. The main goal of an architecture based system of Machine Learning, that will aid in understanding CLE behaviors, deep learning models and Computational Psychometrics (CP), including using Convolution Neural Networks (CNNs) to recognize patterns, identify skills, and extract features.

Keywords*: machine learning, Computational psychometrics, skills, deep learning and collaborative learning.*

I. Introduction

Since research suggests that active human involvement in macro and micro group discussions is essential for effective learning, collaborative learning techniques have been widely adopted by organizations at all stages Lei et. al[1] current study although utilizing mathematical models to simulate human behaviour has been done for a long time, In the second step, computational psychometrics (CP) and deep learning based on convolution neural networks (CNN) are employed to carry out feature extraction and cloud computation. Third stage: Using the parameters measured in the first two steps, comprehend, abilities, and collaborative behavior at the micro level. The third phase incorporates machine learning for efficient group dynamics assessment and visualization, including precisely measuring the improvement in the groups' level of common awareness of various points of view and ability for debunking misconceptions. Our paper is organized as follows: Section II provides a brief overview of related work on multi-modal human interaction analytics using machine learning. Section III discusses the functional component design and three-stage architecture for large-scale CLE. Section IV discusses scalable uses of our architecture for the Departments of Homeland Security (DHS) and Defense (DoD), as well as next-generation collaborative learning and assessment systems. Section VI's recommendations for additional work and conclusion.

II. Related work

Recently, the machine learning (ML) and artificial intelligence (AI) communities have been hard at work proposing and publishing cutting-edge approaches for processing and analyzing multimodal data relevant to human behavior. Due

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to page limitations, we will not be able to explain and recognize all of these works; nevertheless, we will provide a few brief highlights of our own work. Khan [6] provided a method that makes use of multimodal telemetry information from two pilot experiments in the areas of collaborative learning and participant analysis temporal dynamics of behavioural patterns. Polyak et al. [7], [8] presented the use of CP for CPS skill measurement. They used data from actual behavioural and post-game investigations for machine learning analyses. They built their CPS game tasks according to W. Camara et al.'s Holistic Framework (HF), which is tied to the psychometric standards of Evidence-Centered Design (ECD)[9] for ACT.

III. Methodology

As a result of massively scaled, high-performance, data-intensive computing, our ability to collect and analyze data in a variety of formats is changing. Data-intensive computing changes the way we think about education, research, and technology since it makes advanced data collection and computing easier. C. Chen et al. Data-intensive scalable computing has a high potential for novel applications. This will get increasingly difficult if the platform is scaled up to handle massive datasets. The ability to visualise such data has advanced significantly thanks to recent advances in computation. The use of data analytics and visualisation will be an important instrument for the verification of Data Processing and Integration The objective of data analytics and computation architectures is to establish identities from huge quantities of CLE interaction multimodal data gathered from various sources. Large volumes of CLE multimodal interaction data, acquired from many sources and containing the identities of people, machines, sensors, etc., will be processed using a number of solutions built on the Hadoop data analytics platform. This arrangement takes into account the user's input data, such as eye tracking and behavioural models, as well as the user's identity, including username, email, true name, gender, eye colour, and fingerprints. C. Piech [12] [13]. ACT's enterprise learning analytics platform (LEAP) will be used to conduct deep learning in the cloud using Python/R. We intend to deploy a feature extraction method based on CNN-based deep learning for skill, pattern, and trend recognition, as well as to achieve state-of-the-art feature classification accuracy. We intend to upgrade this network topology over time in order to create a dynamic system.

A. Cloud Data processing: In HPC, we use a method for dynamic process partitioning. The network updater adds new network-specific data entries in response to any real-time events, such as changes in the team's activity and makeup. CP: Computational Psychometrics Collaborative problem solving (CPS) is one of the cross-cutting competencies in ACT's Holistic Framework, which provides a thorough explanation of the skills and knowledge people require to succeed in the twenty-first century, at work and in school. New CPS pathways have been established as a result of sophisticated computational methods and analytical techniques. Researchers in the field of psychometrics began creating tests at the same time, employing cutting-edge computing methods and analytical tools. This new, well-known interdisciplinary field of study is known as "Computational Psychometrics (CP)". The goal of CP is to

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quantify learners' latent skills in real time by using theory-driven psychometrics, stochastic theory, data-driven machine learning, and information querying. CP is a brand-new field of learning and assessment (LAS) research. As shown in Fig. 1, the compute cluster combines CP and CLE components.

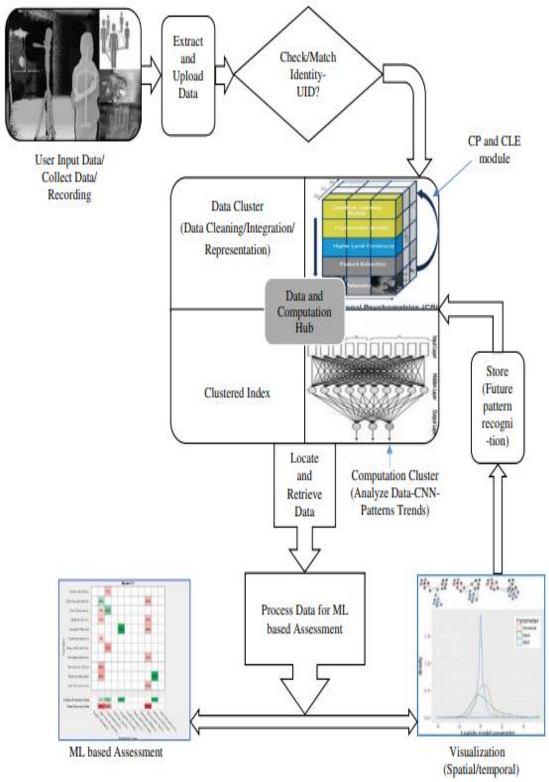

Figure 1: Framework for machine learning-based data demanding computing and efficient evaluation.

B. Eff Assessment: The effective assessment part uses the CNN and CP modules shown in section II-B to identify and retrieve data once the calculation is complete. The CNN and CP modules mine two-player dyadic gaming recordings and behavioral data for features, train models, and uncover patterns. We seek to research human behavior as it relates to certain gaming settings in order to understand the dynamics of group behavior at the micro level, such as shared knowledge and involvement. In order to attain our goals.

Real-time data correlation (correlation of abilities, attainment level between groups), situational data processing, and regular and important event/person analyses are performed, among other things. In this study, we use machine learning to examine user (node), interaction (link, weighted flow), knowledge (skills/abilities), local and global system features (engagement, common understanding), behaviors, group density, cluster formation, and the significance of collaborative learning network properties. Another function of the EA module is predictive decision-making based on group behaviors. In order to facilitate effective group interactions, performance visualization, and exploratory analytics, this module stores potentially valuable patterns from the past and present.. Biometric data is evaluated for biometric database matching and biometric image processing.

Y. Yang et al[15] propose that unique physical qualities known as biometric data, such as a person's face, iris or eye tracking data, or fingerprints, could be used to automate recognition.

C. IV.PRELIMINARY INVESTIGATIONS

This section covers some of the early stages of experimenting.

CIS is a two-player (dyadic) CPS game that takes place in a collaborative learning environment (CLE) with participants in various rooms who can communicate via Skype and, if wanted, the in-game chat option.

The above-screen webcam with an integrated microphone will be set up exactly in the rooms.

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The laptop will also be equipped with a wireless mouse and keyboard.

According to Fig. 2, this study concentrated on gathering the following information: time spent in-game and between games, behavioural expressions, item clicks, chat logs (conversation flow).

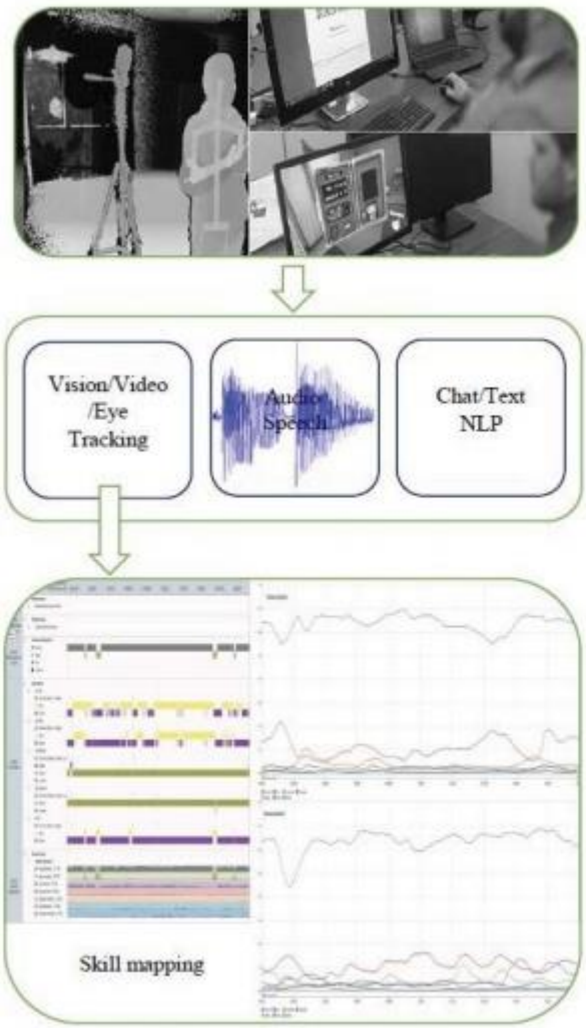

Figure 2: CLE multi-modal data analytics and skill mapping process.

As illustrated in Fig. 2, We extract four sorts of data files from two-player CPS game interactions: video, eye tracking, audio, and chat/text. All of these source files are then used for identity matching or naming convention purposes. Then, for feature extraction, correlation, and pattern recognition, we use CNN-based machine learning analysis. In order to create different behavioral markers and emotional states for dyadic games, we employed Analysis of video clips using face reader and observer analysis (see third block in Fig. 2). Fine-grained data from numerical and behavioral investigations is also analyzed using the MATLAB Statistics and Machine Learning Toolbox. We conducted an in-depth learning analysis. We then used these behavioral indications and emotional states to map the CPS teamwork skills.

IV. CONCLUSION AND FUTURE WORK

In order to identify signs of collaborative aptitude using the CLE's behavior, group dynamics, and interactions, we developed a machine learning (ML)-based system architecture. We created a three-stage architecture for computing data-intensively and measuring CPS teamwork effectiveness. We propose to develop text-based Natural Language Processing (NLP) / Machine Learning (ML) models to detect or categorize distinct CPS sub-skill performances using chat logs, audio/video interactions, and other data collected throughout the research. At this level, additional feature extraction for CNN-based pattern recognition is used. The data gathered while developing this baseline model will play a crucial role in directing subsequent stages and prospective studies.

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