Results

Ultimately, the objective of this research was to develop an intellectual in-game algorithm for rock, paper, and scissors who would be able to distinguish and overcome her/his opponent's patterns of natural gameplay. As a result, a dataset was developed in tandem with the study using CNN's multiple ML and deep learning models. Images from OpenCV and also Matplot are transitioned from Blue-Red-Green (BGR) to Red-Green-Blue (RGB). Then the MediaPipe and Haar Cascade being used as effective tools to identify complicated hand gestures accurately. With the use of 6,000 preprocessed pictures, three-hand gestures were employed in the game to pit not only one player against another but also a person against artificial intelligence (AI).

We were able to get the best results by utilising real-time hand monitoring and adaptive magnification of the hand frame. Our model recognised when the hand went forward or backwards, and all photos were scaled to the specified dimensions before being captured and saved. All of this contributed to a more precise identification of the hands. During this particular brainstorming session, the only topics discussed were the pictures presented through Mediapipe and the scaling and storing of the dark background image.

As a result, we didn't have to create a CNN from the ground up, which reduced the amount of time it needed to gather and utilise information. A vast number of layers and several variables were used in training CNNs: filters, kernel size, strides, padding, and activation having values of 32, (3, 3), (1, 1), "same" and "ReLU" respectively. The use of minimum computer resources resulted in a model which was trained in less time than current and existing best practices. The use of blurry and flickering images of the hands helped recognise their motions better, i.e., rock, paper, scissors.

Our results were ideal at 30 fps because of our extensively trained model, which attained 99 percent accuracy for the classes, exceeding state-of-the-art performance, and precisely describing hand movements. One class achieves the highest f1 value of 1.00, while the other classes have f1 values of 0.99 and 0.98, respectively. Precision and recall were identical to those of the f1 score.

We can see in Table\_\_ that Model 3 employing RNN coupled with LSTM and GRU achieved the greatest prediction performance, not only in training but in the testing sample for our RNN gaming prediction models too. Contrary to any other algorithm, our ultimate accuracy of 0.94 is the best we've ever achieved. As a machine learning model, model 2—Multi-label Classification through an SVM—did pretty well, as demonstrated in the classification report. It doesn't perform as well as RNN, which was due in part to anomalies detected in SVM, but after eliminating them, it effectively predicted. By far, the greatest results from an ML model are achieved by this machine learning model, which has an efficiency of 81 percent on the training dataset and 60 percent on the test dataset.

First, we notice an accuracy of 80% on the training set and a little over half that, 48% on the testing set for our first model, the Markov chain model that combines preceding series based on its preceding series. There is a significant research gap, which we want to address with this project in the future, and we expect to develop a new kind of ML model with an accuracy comparable to that of an RNN model.

For the training and testing data, the precision for predicting the "left player's wins" is above 88% and 70%, respectively, while the "right player's wins" and "the gameplay ties" are predicted to be over 100% for both training and testing samples. Moving forward, we want to work on increasing the recognition accuracy and adding dynamic gestures like swiping up and down, as well as exploring alternative hand-held or finger-game possibilities.