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REVOLUTIONIZING E-LEARNING: AFFECTIVE STATE MONITORING THROUGH HYBRID DEEP LEARNING MODELS

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Abstract: The COVID-19 times was one of the most revolutionary times that made many changes in education society such as transferring the learning process from in-person to virtual learning environment. The virtual learning environment came with its own advantages and disadvantages. Advantages such as remote access of the lectures, consistent learning etc, but it came with tremendous disadvantages such as lack of self-discipline, social isolation and limited interaction which made everyone realize the importance of teachers in-person interaction and learning. This research gives the best solution available by using bagging (bootstrap aggregating) ensemble learning with 1D convolutional neural networks (1D CNN), 1D residual networks (1D ResNet), and hybrid deep learning models. The model uses bagging which helps learning to connect with CNN model and another the ResNet model to evaluate scores on students' engagement detection model. The combination of CNN and ResNet helps the model to make more accurate and stable predictions. This research brings out the solution using DAiSEE (Dataset for Affective States in E-Environments) which monitors the student engagement during the virtual class environment by monitoring facial expressions such as frustration, boredom, lack of concentration etc. Employing these modern models enhances the accuracy and yielding capacity of the model compared to individual deep learning models and hence helps the model to make most accurate predictions. By the development of this model, it enables a proper learning environment which demonstrates an evolution in the modern learning process.

Keywords: Bagging, 1D Convolutional Neural Networks (1D CNN), 1D residual networks (1D ResNet), Deep Learning, DAiSEE (Dataset for Affective States in E-Environments), Virtual learning, Engagement detection model

I. INTRODUCTION

COVID 19 brought many complex and multidimensional changes to the society which led to many challenges in various sectors and one of the sectors which was deeply affected by it was the education sector [3]. The enhancements in communication technology made available for the best solution which were transferring the in-person education to an e-learning environment. Consequently, due to the digital technology at use, online learning is shifting the education model as it is today and how it will be tomorrow. In contrast, it minimizes the importance of a location or a set time slot attached to traditional classrooms and time-tabling systems needed for classroom learning. Furthermore, because the lessons and other teaching materials are made electronically retrievable, the learners are free to revisit a given material as many times as they desire, depending on how often they feel the need to.

The key element of effective learning is the two-way interaction which can be possible in the both the settings offline learning as well as the e-learning environment. However, it challenges to achieve this interaction or communication in the online e-

learning environment [5]. The lack of information for the teacher about the student's attention, engagement or focus becomes one of the biggest challenges for the effective learning. Effective learning starts with an active engagement as engagement is an internal feeling that comes from the mixing of various internal signals and it is obvious that these emotions are not physically identifiable with normal human eyes. As engagement focuses on three key aspects that are behavioral, emotional, and cognitive aspects making this research initiates to detect students' engagement crucial to enhance the learning process.

The proper assessment of a student's learning is a continuous process which plays a vital role in properly analyzing the student's growth and engagement in an e-learning environment [6]. The e-learning platform provides the student-centered learning (SCL) environment which uses formative evaluation throughout the learning process rather than old-school summative evaluation methods. The old-school summative assessment method provides limited feedback for improvement, focuses on outcomes over the learning process, and can increase

stress due to high stakes whereas the formative evaluation method targets on giving continuous feedback, helping students improve and guiding teachers to adjust their instruction for better learning outcomes. Hence, there arises a need for an automated approach capable of state monitoring the levels of student engagement, overall supporting the sustainable improvement of the learning process.

This assessment of a student's learning in an online environment needs many parameters to be identified such as analyzing facial expressions, eye contact, body gesture, etc. In order to make this assessment effectively the Social Signal Processing (SSP) plays an important role, SSP is a field that empowers computer with the ability to sense and understand nonverbal human emotions including facial expressions, eye contact and body gestures. By capturing and analyzing these social signals, SSP can make interactions with technology feel more natural and allow deeper insights into human behavior. Combining Social signal processing with the Deep learning concepts such as convolutional neural networks (CNN) for classifying the image or video data, Ensemble learning which combines multiple algorithm such as Random Forest to make more accurate predictions, bagging to improve accuracy of the prediction, DAiSEE which provides a dataset for the analysis of various facial expressions. The setting of this model introduces multi-

model deep neural network (MDNN) which integrates facial expressions and gaze direction along with LSTM (Long short-term memory) for analyzing head pose and facial actions [1].

This study introduces a new method for the identification of engagement of students in Virtual Learning Environment using bagging combined with deep learning models including 1D convolution neural network (CNN) and 1D Residual Network (ResNet)[1]. By integrating these models with bagging, this method enhances the accuracy and steadiness required for proper detection and engagement.

The technique of bagging, which is an ensemble method, improves generalization capability and decreases the degree of overfitting by making further predictions from more than one neural network that had been generated with different subsets of data. This research uses bagging to combine CNN and ResNet, utilizing the strengths the two models have to offer. CNNs work well in capturing spatial structures or patterns from the image data and hence are good in detection of facial expressions. ResNets is effective in removing vanishing gradient problems as it allows deeper networks with use of shortcut connections. In combination, CNN and ResNet form a powerful paradigm that results in a more accurate learning process and overall, more exact engagement predictions.

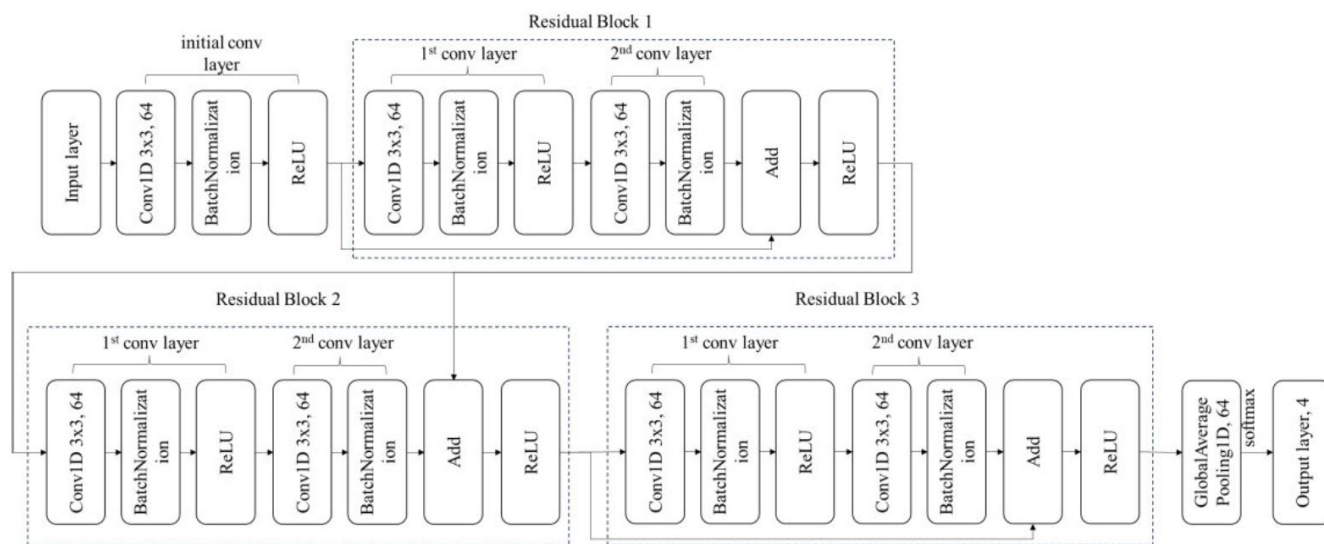


Figure 1: ResNet architecture [1]

The data set used in this research is DAiSEE (Dataset for Affective States in E-Environments), a recently developed data set for DSfAeE (Dataset for Affective States in E-Environments), which consists of videos of instructional classrooms that have been annotated for engagement factors such as frustration, boredom, and attention. These expressions being tracked, the model reveals in real time the engagement variations; the respective information is useful for educators to adapt their teaching approach based on the students' needs.

All in all, incorporating CNN, ResNet, and bagging in this research contributes to a new and innovative method of tracking engagement in virtual education. This approach benefits not only in increasing the accuracy and stability of the DNN but also in giving clear recommendations to educators about students' affective states. The resulting model thus entails a better form of adaptive and responsive online learning environment, and thus the congruence of ensemble and deep learning techniques can be inferred regarding the potentials of

educational technology and affective computing.

The deep learning model will be initially employed to learn from the different facial engagement and hence the weights (The parameters which are learned by the model) are used afterwards for the initialization of the model which will recognize the student's engagement in an e-learning environment. The outcomes of this engagement model will be comparatively analyzed with the deep learning models like CNN and VGGnet along with some traditional learning models such as HOG (Histogram of Oriented Gradients) + SVM (Support Vector Machine) which will help to identify and compare the outcomes from the model. The accuracy after the employment of the model is expected to be around 75% - 80%.

II LITERATURE SURVEY

A| MONITORING THE FACIAL EXPRESSIONS IN E-EDUCATIONAL SYSTEM

Continuous monitoring of a student's facial expression is always needed for proper communication and analyzing whether a student is actively involved during the session or not.

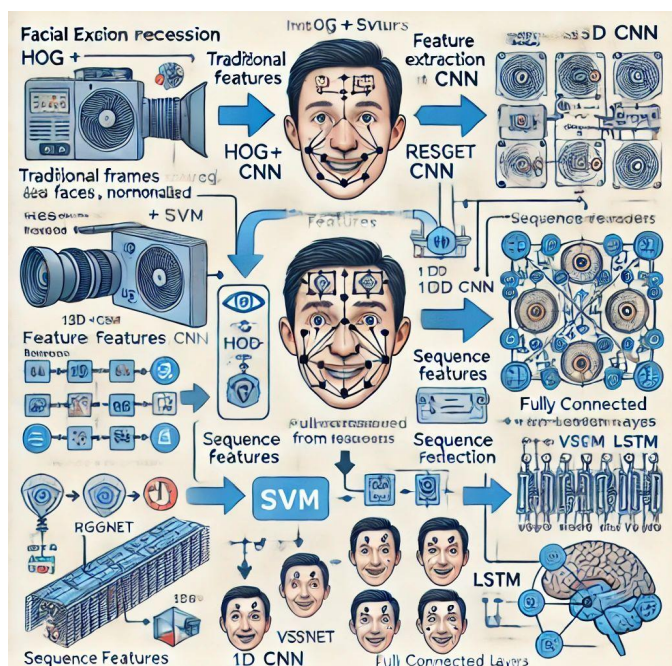


Figure 2: Working of model

The evolution from real life education to an e-learning environment came up with many changes and challenges and hence lack of communication gap between students and teacher started playing its role in the e-learning environment. The Covid-19 times was of the transforming period of student's life and this evolution to e-learning environment resulted in many students started losing their attention span and concentrating ability and hence students started facing significant setbacks in their learning process[4].The study of (Hongsuchon et al. 2022) (Gopal, Singh, and Aggarwal 2021) clearly represent the changes in students attention span over time after Covid-

19.Hence the building of the online engagement monitoring model bought another revolution in the tough times where everyone was lacking in communication. This research mainly focuses on improving the accuracy of the model and helping it learn in a sustainable way.

ONLINE ENGAGEMENT MONITORING MAINLY ENCOMOPASSES OF: -

- 1) AI and Deep learning
- 2) 1-D CNN and DAiSEE
- 3) ResNet and VGGnet
- 4) Ensemble learning and Bagging
- 5) Privacy issues
- 6) Accuracy

B| AI and Deep Learning

Facial detection tools have AI as their major component, and the primary subset of AI is Deep learning. It allows the AI model to understand facial expressions, categorize them into active, bored, frustrated states, etc., and make the correct predictions [22]. Fully connected networks and the most commonly used architecture in Image processing is Convolutional Neural Networks (CNNs) and these are critically important for visual recognition. The CNN based systems employ methods such as VGGnet, ResNet for transfer learning, Polling layer and convolutional filters for feature extraction, ResNet for residual connections, ensemble learning and CNN-RNN hybrid model.

C| 1-D CNN and DAiSEE

1D CNNs and the DAiSEE dataset are both used in completely different aspects in the field of emotion recognition and facial analysis but equally important despite the fact that the DAiSEE dataset is a dataset which provides the model with the variety of different facial expressions and it has nothing to do with the technical aspects by which a model is built.

1-D CNN:-

1-D CNN is employed to process the sequential data and 1-dimensional pattern and it is usually employed with LSTM and SOFTMAX function. In facial recognition the CNN architecture processes the temporal data such as lip movement, muscle activities, eye blinks, etc. which makes it more useful in facial expression understanding and identifying behavioral traits. In facial recognition 1-D CNN extracts the information form the images/video frames and convert it into one-dimensional format. Images can be converted from matrices to vectors and each vector will represent one feature or pixel intensity or even one layer of convolutional layers through which the CNN can master the features that differentiate between different facial expressions.

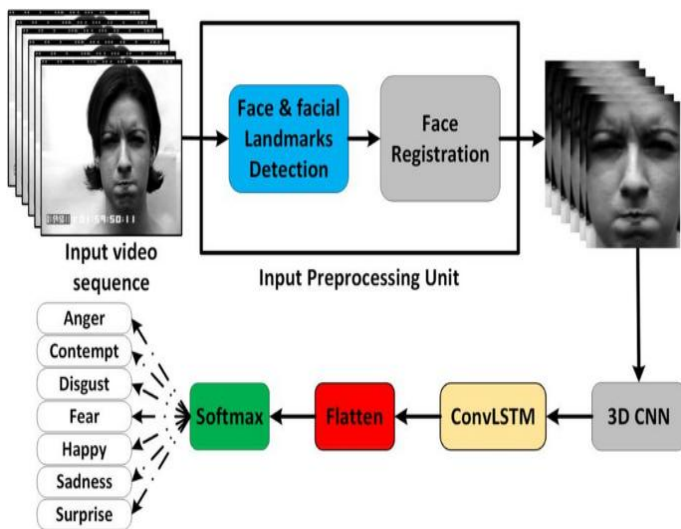


Figure 3: 1-D CNN Working [1]

1-D CNNs can help to detect changes in facial expressions over time, which may help in emotion detection. We prefer using 1-D CNNs over traditional methods because unlike standard CNNs that operate on 2D images, 1D CNNs simplify the input structure by focusing on sequences [15]. This can lead to faster processing times and less computational complexities and also it enables automatic feature extraction without using manual preprocessing

DAiSEE :-

DAiSEE is a multi-label video classification dataset designed to recognize user affective states, including boredom, confusion, engagement, and frustration. It comprises 9,068 video snippets collected from 112 different users. This dataset was the crowd sourced dataset which was then validated against a standard created by expert psychologists [20]. This DAiSEE dataset has some of its key features as multi-label classification where each video from distinct peoples contains variety of effective states, it also the feature of diversity in the database as it contains 9,068 video snippets collected from 112 distinct users [14].

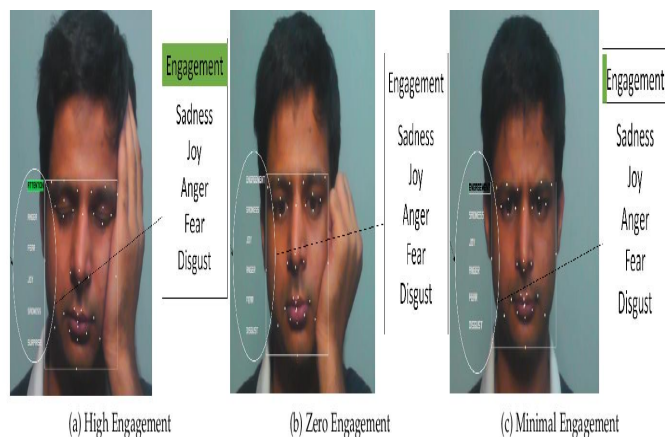


Figure 4: Sample snippet from DaiSEE

DAiSEE has a significant role in building an effective and accurate student engagement monitoring model because of its diverse database. It provides the model with the rich dataset of different emotions and hence helps the model learn, furthermore it helps the model to distinguish between different facial expressions during an online class or a e-exam environment.

D] ResNet and VGGnet

The ResNet and VGGnet are two prominent architectures used in Facial Expression Recognition (FER). Both of them show significant effectiveness in extracting the features from images/video snippets. As deep learning continues to evolve, ResNet and VGGnet will continue to contribute in integrating new models for Facial Expression Recognition (FER).

ResNet:-

The training parameters used in the ResNet model are batch size, learning rate, and optimizer with the same parameter values as the CNN model. Furthermore the ResNet architecture is used for deep feature extraction (observing even the small movement in facial activity), residual connections (skips one or more layer and directly passes the information to deeper layers and solves the problem of vanishing gradient) and transfer learning (fine tuning a pre-trained ResNet model on a specific facial expression dataset) [19]. The Resnet model shows the accuracy of approximately 81% whereas the alexnet model gives the accuracy of approximately 86% so it's better to use alexnet.

VGGnet :-

The VGGnet is a deep convolutional neural network which is known for its simplicity. It uses a filter of size 3 x 3 which helps it to learn the features of an image more deeply. This property of VGGnet makes it more suitable for tasks like image recognition. VGGnet has a deep architecture which consists of multiple layers mainly 16 or 19 layers (VGG16 or VGG19) which helps in extraction of complex features during image recognition which furthermore is useful for accurately classifying the distinct emotions and effective state [2].

In VGGnet as the image passes through the network each layer extracts the feature increasingly. Each layer detects the features like edges, texture, etc. whereas the deeper layers capture the complex features such as shapes and patterns. After each convolutional operation the ReLU (Rectified linear unit) activation function is applied which brings the non-linearity to the model. Following the convolutional operations, VGGnet engages max pooling layers where pooling operation decreases computational load and mitigates overfitting by reducing the spatial dimensions of feature maps and extracting the most significant facial features. The VGGnet is known for its high accuracy with an accuracy rate of approximately 92%, transfer learning and its versatility.

E] Ensemble Learning and Bagging

Ensemble learning is a process of combining multiple models to produce a single accurate prediction. This approach strengthens the various algorithms to mitigate the weaknesses of individual models. The ensemble learning approach improves the model's performance by predicting a person's facial and emotional expression more effectively. This research aims to develop an efficient model which will analyze student's engagement in e-learning format using bagging ensemble learning.

Bagging is an ensemble technique which enhances the stability and accuracy of machine learning algorithms (particularly decision trees). Bagging creates a distinct subset of training models through a process called bootstrapping. Each subset is then used to train an independent model which learns from its own data. Once the training is completed, averaging (for regression) and voting (for classification) are combined for models' predictions to create a compiled prediction. Hence, bagging reduces the risk of overfitting. The model approaches effective state monitoring in student engagement in e-learning video recordings which uses bagging ensemble learning, an ensemble deep learning method.

F] Privacy Issues

During the state monitoring for facial expression recognition through online learning video recordings, there may occur prominent privacy issues as from the point of view of the learner. E-learning platform records classes which might capture a learner's image containing their personal details without consent which raises privacy concerns as the personal recordings may be shared or stored. These recorded videos are transmitted over the internet and if no proper security measures have been taken,

undesirable third parties have a chance to hack their personal details through the video material [21]. There are chances of peer privacy concerns i.e., other learners or participants can take screenshots or video recordings of the other, and those recordings can be shared without your permission.

G] Accuracy

Accuracy is nothing but the rate of success of a model once it is completely out in action. The model needs to be accurate and efficient in the tasks it is going to perform. This online engagement monitoring model uses variety of deep learning architects such as 1-D CNN for image feature extraction, DAiSEE which provides a rich dataset for different emotions, ResNet and VGGnet to enhance its capabilities for the accurate predictions. Using all these architects increases the accuracy of the model and in result the model can yield the accuracy of prediction up to 80%.

III METHODOLOGY

Figure 5 shows the proposed bagging ensemble learning model. Each video from the DAiSEE dataset undergoes extraction into 300 frames. The tool used for the feature extraction process is OpenFace library, providing numerical vectors consisting of 709 facial features [12]. From this set of 709 facial features, a deep feature extraction process ensures to identify key features from facial expressions, enhancing the accuracy and prediction of the model. This technique involves the application of Singular Value Decomposition (SVD). SVD method helps in simplifying complex data by breaking it down into several parts and each part explains the variance in the dataset.

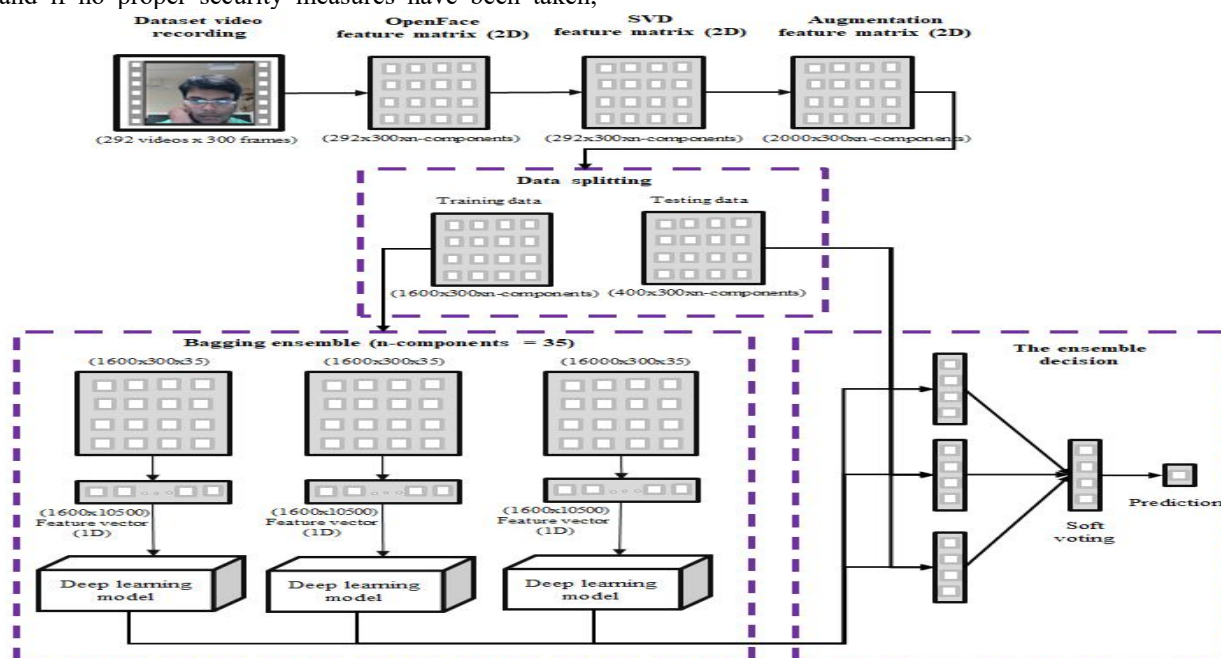


Figure 5: Proposed Bagging ensemble learning model [1]

As the research progresses and the bagging ensemble learning is introduced, it demands for the additional resources, the data is

transferred from the 1D vectors after the bagging process to enhance computational accuracy. Any information that is lost during this

process will be addressed in the facial feature extraction process using OpenFace Library.

A.DATASET

The video snippets from the rich dataset of the DAiSEE consists of affective state levels of boredom, confusion, engagement and frustration. Boredom is defined as a feeling of tiredness or restlessness due to lack of interest. Confusion is defined as a state where someone is lacking in understanding the concept being taught. Engagement is the state of interest arising from the involvement in an activity.

Table 1 is a snapshot of the data labeling for each video in the DAiSEE dataset [20]. Each video shows the level of the student's affective state denoted in numbers, 0 for very low, 1 for low, 2 for high and 3 for very high. For example, the video with clipID 1100011004.avi has the Boredom level of 0 (Very Low), Engagement level of 3 (Very High), confusion level of 0 (Very low) and the frustration level of 0 (Very Low), hence the person in this clipID is highly active and engaged.

B.DATA SPLITTING

The data is split into two: training data and testing data. The test data is used to test the performance of the deep learning model generated from the training data. The testing data is used to evaluate the final result obtained from the training of the data. The training data will be divided into two parts namely training data and validation data. The proportion of training, validation, and testing data is 64%, 16%, and 20%, with 1280 training data, 320 validation data, and 400 test data, respectively. To ensure that each data distribution is in the normal distribution, it is necessary to visualize the data distribution in each class. In Figure 6, it can be seen that the data is normally distributed [1].

C.BAGGING ENSEMBLE APPROACH

A bagging ensemble is a type of ensemble learning that uses various models of the same algorithm and they are trained on the same dataset. The results from each model are combined to make a single final prediction using soft voting technique. Soft voting uses two approaches namely averaging soft voting and maximum soft voting. Averaging soft voting is the technique used in ensemble learning which takes the average of the results from different models and makes a single prediction. While maximum soft voting is a technique which makes the ensemble decision by taking the highest probability from each model

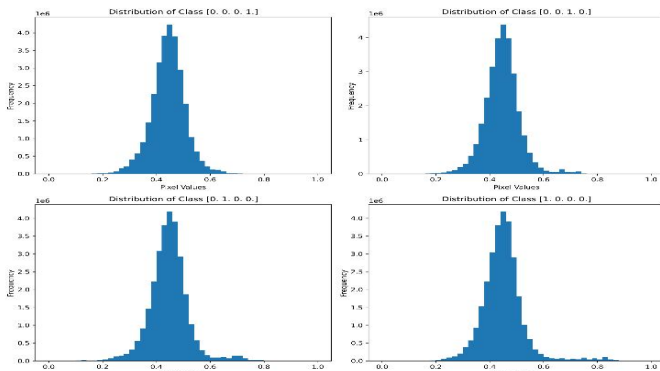


Figure 6: Data distribution for each class [1]

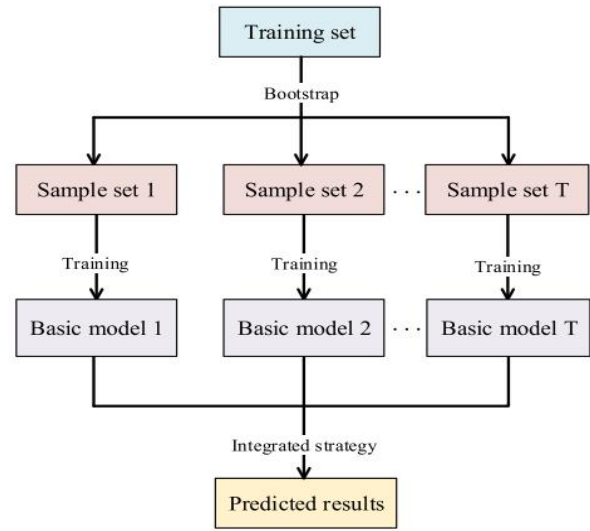


Figure 7: Bagging Ensemble [1]

Figure 8, model 1 assigns probabilities of 0.5 to class 1, 0.2 to class 2, 0.9 to class 3, and 0.1 to class 4. Using only model 1, the prediction would be class 3 based on the highest probability. This process is similar for models 2 and 3. In ensemble bagging, the probabilities from each model are averaged for each class, resulting in a new probability distribution used for prediction.

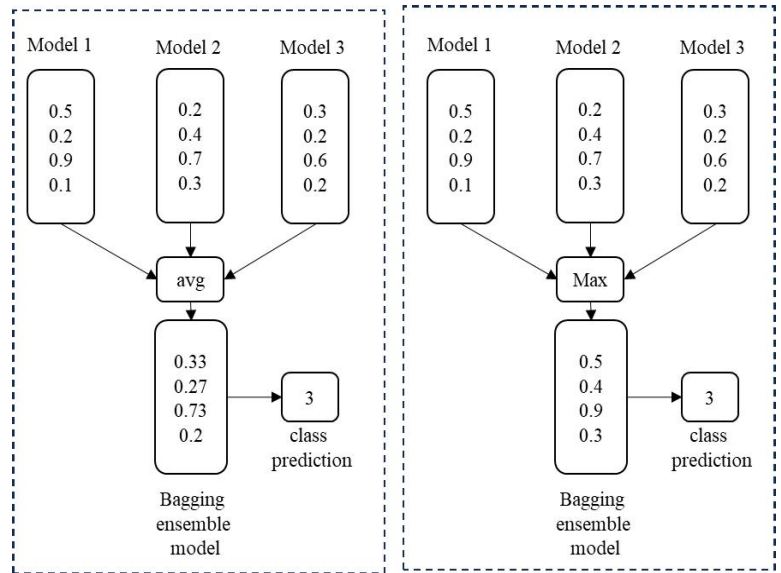


Figure 8: Soft Voting in Ensemble Decision, left for averaging soft voting [1]

IV.RESULT

This research develops detection of students' engagement by bagging ensemble learning on CNN, ResNet and hybrid models. In the first dimensionality reduction step is applied in order to extract important features among which 35 components proved to be the best since it retained 99.99 percent data information. The study recommends optimal batch size to numbers of 64 for CNN and 32 for ResNet with no remarkable accuracy variance between the two.

Despite being inferior to bagging, both models improved accuracy due to CNN improving from 90% to 93.25% and ResNet from 90.25% to 93.75% when bagging ensemble learning. Other metrics such as precision, recall and F1 scores also saw enormous

improvements particularly when soft voting was used over the norm.

The hybrid bagging ensemble of CNN and ResNet gives a bagging accuracy of 94.25% which beats both the individual models and the ensemble model. Bagging helps to combine the prediction of several models so as to reduce the bias and variance thereby producing a more accurate and stable result. The results substantiated the claim that ensemble techniques are useful in making predictions that are deep and accurate.

V.CONCLUSION

Virtual teaching and learning environments, fueled by the emergence of COVID-19, have altered the educational landscape irrevocably. This research highlights the dual nature of this shift, presenting both advantages, such as remote access and consistent learning, and significant challenges, including social isolation and diminished student engagement. In order to overcome these challenges, the paper presents a novel method that is based on hybrid deep learning models, in particular, bagging ensemble learning integrated with 1D Convolutional Neural Network (CNN) and 1D Residual Network (ResNet).

These models enhance the accuracy and stability of student engagement detection by effectively analyzing facial expressions and other nonverbal cues, which are critical for understanding student involvement in an online setting. By the integration of the DAiSEE dataset, the model is further enhanced for detection of different emotional conditions, including frustration and boredom, which consequently, provide important information for student behaviors. The research anticipates achieving an accuracy rate of approximately 75% to 80%, demonstrating the effectiveness of the proposed methods.

In addition, the paper focuses on the significance of recurrent assessment in e-learning and argues for continuing assessment approaches in e-learning with a focus on continual assessment by means of formative assessment rather than top-down assessment methods. Using these contemporary methods, the focus of the study is to help create a more interactive and efficient learning environment and thus to achieve a long-term, sustainable improvement of the process of learning in a post-pandemic world. In this work not only immediate needs are addressed, but also future development in the field of "online learning" is created.

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