https://doi.org/10.31449/inf.v48i18.6420 Informatica **48** (2024) 21-34 **21**

Evaluation of Mental Health Education Using a Northern Goshawk Deep Multi-Structured Convolutional Neural Network for Emotion Recognition

Yuanyuan Duan
Shanxi Conservancy Technical Institute, 030032, 345 Malianying Road, Xiaodian District, Taiyuan City, Shanxi Province, China
E-mail: 18734530156@163.com

Keywords: discrete wavelet transform (DWT)**,** emotion, education, mental health, northern goshawk deep multi-structured convolutional neural network (NG-DMCNN),

Recieved: June 18, 2024

Student learning and development of emotional control abilities are aided by mental health education. It makes it possible for students to understand the sensations and emotions better. Students' mental health and negative emotional responses can help to quickly resolve psychological issues and prevent them from interfering with their regular academic programs. In this study, we proposed a novel Northern Goshwak deep multi-structured Convolutional neural network (NG-DMCNN) to recognize studentsemotions related to mental health education. For this study, 300 participant'sfacial and physiological data were acquired. Pre-processed data using Kalman filtering is an advanced method for data noise reduction. The NG-DMCNN method is compared to the other traditional algorithms. Significant performance metrics were attained by the NG-DMCNN model: recall of 78.42%, accuracy of 94.56%, precision of 92.38%, and F1-score of 89.67%. The result shows the psychological stress test indicates that the students are in good health and not performing well. The proposed method hassuperior performance than other algorithms. The study intends to offer a more accurate and effective method for health education.

Povzetek: Razvili so NG-DMCNN model za prepoznavanje čustev študentov v kontekstu izobraževanja o duševnem zdravju, ki omogoča boljše razumevanje čustvenih stanj in prilagajanje izobraževalnih pristopov.

1 Introduction

One of the biggest and trickiest medical problems in the real world is diagnosing and treating mental health illnesses. When someone is mentally well, their behaviour, thoughts, and emotions are influenced, which affects how they interact with their environment [1]. An essential aspect of the human experience, emotional expression reflects judgment and intelligence, facilitates interpersonal contact, and conveys perceptions of events. A person's psycho-physiological and psychological status can be inferred from their emotions. Due to their emotional states, many people experience depression, which has serious consequences for psychological health [2]. The most widely used method in Facial Expression Recognition (FER) classifies fundamental emotions because of its simplicity and universality in describing facial expressions. But to handle the facial emotions, several models currently provide a broader range of emotions. Restructuring current behavioural techniques in response to important events of different intensities and shapes is necessary [3].

Just over one-third of the numerous college students who report mental health issues obtain therapy for psychological problems. One of the biggest obstacles to college students receiving mental health care is their ignorance of the services on campus. Children with mental health disorders may experience sudden behavioural changes as a result of socialization and interaction problems, which may affect how they see the world and socialize [4, 5]. College student suicide rates and school dropout rates are high as a result of these problems. Since there is evidence of a high frequency of mental health disorders among college students, many universities have responded by introducing initiatives to teach mental health through lecture series and mental health counselling [6].

Compared to the old education approach, teaching mental health through network education at universities is more in track with how modern society is exchanging. The importance of teacher emotions and how they affect student outcomes is becoming more and more apparent [7, 8]. Instructor feelings are a component of a system that affects and is affected by student outcomes, which also includes the feelings, ideas, and actions of the students themselves. The potential benefits of emotion recognition research for mental health education have prompted interest in the field. In the early stages of diagnosis and evaluation, an emotion recognition system could help physicians by providing objective emotion detection [9, 10]. In situations when it's important to comprehend pupils' emotions, it could be utilized for diagnosis and therapy response tracking. In mental health education, identifying students' emotions highlights potential shortcomings in existing methods while fostering a deeper knowledge of their needs and experiences. To overcome this, we present a novel Northern Goshawk deep multi-structured Convolutional neural network (NG-DMCNN) to identify students' emotions on mental health education.

2 Related work

In this section, we analyze the previous research methods, algorithms, and findings. Table 1 represents the summary of related work.

Table 1: Summary of related work

REFERENCES	Methods/algorithm used	Data size	Result
[11]	A brand-new DNN architecture that classifies emotional states from facial photos by combining Linear Discriminant Analysis (LDA) with AlexNet's Fully Connected Layer 6 for deep feature extraction.	Five benchmarking databases, JAFFE, KDEF, CK+, FER2013, and AffectNet, they covered a variety of sets from controlled situations to photos in the wild, are used to test the framework.	Comparing the suggested method against cutting-edge techniques like Vgg16, GoogleNet, and ResNet, shows better efficiency and accuracy in facial expression recognition while consuming less computational power.
[12]	Using galvanic skin response and photoplethysmography signals, a SVM is used to categorize amusement, melancholy, and neutral emotions, while random forest (RF) recursive feature removal is used for feature selection.	They Utilized video sequences to evoke amusement, grief, and neutral emotions, data were obtained from 37 volunteers utilizing photoplethysmography and galvanic skin response.	When tested on a different test dataset, the suggested model recognized amusement, melancholy, and neutral emotions with up to 90% accuracy, demonstrating its suitability for wearable emotion recognition.
[13]	Identifying arousal and valence levels from fused physiological inputs obtained from respiratory belts, photoplethysmography, and fingertip temperature sensors using RF, SVM, and logistic regression (LR).	Wearable technologies were used to capture physiological signals from individuals who were not identified, with an emphasis on improving ergonomic sensors and simplifying data collection.	Arousal recognition accuracy increased from 69.86% to 73.08% and recognition accuracy from 69.53% to 72.18% with decision-level fusion of the classifiers.
[14]	During Basic Information Technologies lectures, 67 students' facial expressions were examined to identify emotions using the Microsoft Emotion Recognition API and C# programming.	67 students from three departments participated in the study, which looked at how different lecture components and sessions affected the students' emotions.	An examination of the participants' emotions showed a notable increase in anger, fear, perplexity, and contempt at the beginning of the presentation, followed by a noticeable increase in happiness.
[15]	In-depth one-on-one interviews with Experts by Experience, who jointly presented a learning module to nursing	The research concentrated on the opinions and	These results provide insight into the special knowledge and skills Experts by

	students in Europe and Australia, were conducted using qualitative exploratory methodologies.	contributions of Experienced Experts in Mental Health Nursing Education about interactive communication, critical thinking, personal healing, and the incorporation of mental health into general health education.	Experience bring to mental health education that hasn't been explored in previous research. As contributions from Expert by Experience continue to grow, it is important to recognize and value their distinct contribution.
[16]	To evaluate the Youth Aware of Mental Health (YAM) intervention in 11 schools in Montana and Texas, the study used an uncontrolled pre-test/post-test design. Before and after the intervention, surveys on help-seeking behaviours, mental health literacy, and stigma measures were administered.	After participating in the YAM intervention, 436 teenagers (286 from Montana and 150 from Texas) completed surveys assessing changes in assistance-seeking behaviours, literacy in mental health and the stigma attached to mental illness.	Beside with enhanced mental health literacy and a reduction in the disgraceinvolved to mental illness, the 436 youths presentedimportantprogresses in three of the five help-seeking behaviours.
[17]	Attention-based in-depth entropy active learning and Natural Language Processing (NLP) to customized mental health therapies. It makes use of a bidirectional Long-short term memory (LSTM) with an attention mechanism for the detection of depressive symptoms and a method based on synonym expansion utilizing semantic vectors to improve training data selection.	Various labelled datasets for Internet-Delivered Psychological Treatment (IDPT) are used in the study, to improve the datasets via emotion-aware labelling while taking into account the vocabulary sizes, data sources, construction techniques, and baseline human performance levels.	By utilizing bidirectional LSTM with attention, the approach was able to attain a 0.85 ROC curve on the blind test set. It used semantic vector-based synonym expansion to improve the identification of depression symptoms from online forum language in an efficient manner.
[18]	It focused on issues unrelated to mental health and connected to schizophrenia by utilizing machine learning to evaluate Reddit postings. Using supervised and unsupervised ML techniques, linguistic features and content topics were retrieved.	Reddit content about schizophrenia as well as posts from non-mental health categories like parenting, fitness, comedy, meditation, relationships, and teaching were gathered.	It distinguished posts connected to schizophrenia from the control group with a high accuracy of 96%.
[19]	They addressed how to incorporate emotion regulation abilities into the classroom in a realistic way, emphasizing the need to give teachers tools and support their professional growth. The Yale Center for Emotional Intelligence developed the evidence-based RULER approach, which	They focuses more on real-world applications and case studies than on quantitative data, it does not provide a data size. It highlights the theoretical underpinnings and real-	It highlights the possible advantages for academic success, stress management, job happiness, instructor efficacy, and school preparedness.

	emphasizes direct education and incorporation into existing courses.	world applications of emotion-regulating abilities in learning environments, illustrating RULER's strategy for advancing emotional intelligence theory-based social and emotional learning (SEL).	
[20]	They discussed using neuroscience to study brain mechanisms and comprehend the connections between emotions and cognition.	It makes recommendations for how to enhance learning settings based on their findings and implies that understandings neuroscience may shed light on how emotions affect learning.	They investigated to reveal that emotions which are fundamental to our social nature have a big impact on learning outcomes by changing motivation, attention, and memory.
[21]	Evaluations of the ahistorical objectives of social and emotional learning (SEL) for ignoring colonial ties and cultural disdain, as well as unfair institutions that impact communities of colour.	To address suppression, divide and conquer tactics, and systemically imposed self-hatred, it suggests using humanization as a pedagogical and psychological framework. In place of SEL, this paradigm places a strong emphasis on teaching student’s self-knowledge, solidarity, and self-determination.	In contrast to SEL, which is seen as reinforcing current power relations, advocates for humanization as a framework that fosters self-knowledge, solidarity, and self-determination to challenge systematic self-hatred and sub-oppression.
[22]	They Suggests combining life-crafting therapies with Chabot-based mental health interventions in a narrative evaluation. Highlights the use of inclusive curriculum-wide techniques and digital therapy to address students' mental health and academic achievement.	The use of Chabot interventions digital forms of therapy to treat mental health problems in college students. It was in contrast to the life-crafting intervention, which takes a curriculum-wide strategy to improve academic achievement and retention rates.	It suggests that by offering individualized follow-up and coaching, integrating Chabot therapies for mental health with life-crafting interventions may be able to prevent students' mental health problems and academic underperformance.
[23]	For insight into interaction in classrooms at preschools and elementary schools. It examines intervention literature to show how classroom environments, instructors,	To illustrate the practical ramifications of enhancing classroom socializing while emphasizing how it might improve	According to the study's findings, fostering better classroom socializing can raise kids' emotional and intellectual proficiency. It implies that more

	and peers affect students' academic and emotional outcomes.	children's self-control, school engagement, and academic performance.	investigation is required to examine intricate socialization pathways and how they affect teaching methods.
[24]	Online instruction presents a significant difficulty for college instructors amid the COVID-19 pandemic, particularly for English instructors. To achieve this, a BGCN model for the identification of mental health crises were based on the psychosomaticassessmentquestionnaire with its organizational features.	While research studies gauge the frequency and severity of mental health problems among teachers, qualitative interviews shed light on the experiences and perspectives of educators.	According to experimental findings, the suggested BGCN model outperforms neural network algorithms and other ML algorithms in terms of accurateness, precision, F1, and recall.

The primary research questions of this study are explained below,
1. How circumstances do the Northern Goshawk Deep Multi-Structured Convolutional Neural Network (NG-DMCNN) effectively identify and categorize emotions based on physiological and facial measurements?
2. What effects does the NG-DMCNN model integration have on the comprehension and control of participants' emotional reactions in learning environments?
3. With terms of determining students' emotional states, how does the NG-DMCNN model compare to more established algorithms like Bayesian Graph Convolutional Networks, Support Vector Machines, and Logistic Regression in relations of presentation metrics like accuracy, precision, recall, and F1-score?

3 Materials and methods

The dataset was discussed and pre-processed the data using the Kalman filter. Northern Goshawk deep multi-structured Convolutional neural network (NG-DMCNN) to recognize the students' emotions related to mental health education. It is one of the emotion recognition algorithms. Figure 1 shows an overall proposed flow.

3.1 Dataset

In this investigation, the mental health education participant's data were collected. Primarly 300 participants 150 males and 150 girls with an average age of about 20 years contains physiological signals and facial data. The purpose of selecting these data types was to enable a thorough analysis of emotional recognition within the framework of mental health education. The physiological correlates of emotional states including happiness, sadness, anger, fear, and excitement can be understood through physiological signals like skin conductance and heart rate variability.

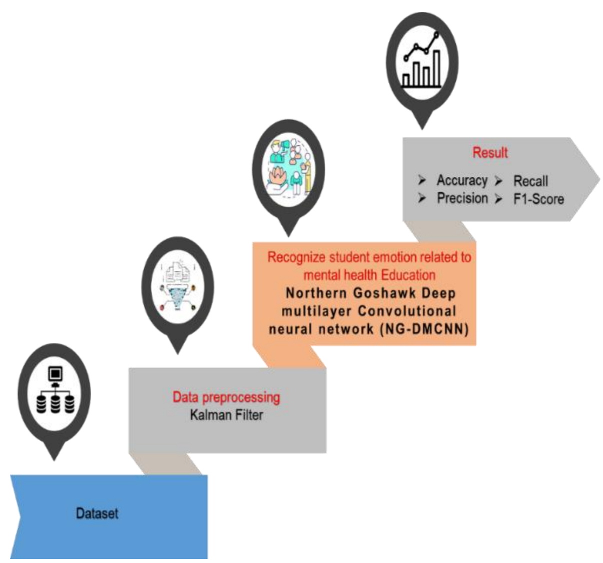

Figure 1: Overall proposed flow

The subtle facial expressions that correspond with these emotions are captured by facial data: a downturned mouth for sorrow, a tightened jaw for anger, enlarged eyes for anxiety, and lifted eyebrows for amazement are examples of these expressions.

3.2 Data Pre-processing

In this section, we pre-process the gathered data using the Kalman filter. This is used for noise reduction.

3.2.1 Kalman filter

In this section, to remove the noise from participant's emotion recognitions we used Kalman filter. According to the Kalman filter, a system on the form generates the noise reduction that has to be filtered.

$$w_{l+1} = e(w_l, v_l) + u_l \quad (1)$$

$$z_l = g(w_l, v_l) + x_l \quad (2)$$

$$.u_l \sim \mathcal{N}(0, R) x_l \sim \mathcal{N}(0, Q) \quad (3)$$

In this case, the system's internal state is represented by w the input is v, output is the z, the process noise is u, and the measurement noise is x. These processes of noise are presumed to have a white, zero-mean Gaussian distribution, with covariance provided by the corresponding matrices $R$and Q respectively

$$\overline{w}_l = \Phi_{l-1}\widehat{w}_{l-1} + A_{l-1}v_{l-1} \quad (4)$$

$$\overline{O}_l = \Phi_{l-1}\hat{O}_{l-1}\Phi_{l-1}^{S} + R_{l-1} \quad (5)$$

$$L_l = \overline{O}_l \mathrm{G}_l^S \left(G_l \overline{O}_l \mathrm{G}_l^S + Q_l\right)^{-1} \quad (6)$$

$$\widehat{w}_l = L_l(z_l - G_l\overline{w}_l) \quad (7)$$

$$\hat{O}_l = (J - L_l G_l)\overline{O}_l \quad (8)$$

For every time step, the Kalman filter calculates the state estimate ($\widehat{w}$)and the state covariance matrix ($\hat{O}$) Equation (1) uses the system model to anticipate the condition one step forward in the moment. The time updates and what this is known as, and it produces a first approximation represented by $^{-}$ and $\bar{O}$this is followed by the measurement update. This yields a posteriori estimate of ($\widehat{w}$)and ($\hat{O}$) by updating the a priori estimate with a measurement with known measurement noise. It is typical for measurements to be made infrequently or at irregular intervals in glucose data collections. Each measurement update is handled by the filter by performing several time updates. The difference between the a posteriori estimates is the same at time steps when no measurement is available.GIs is the measurement matrix, while Φ is the state transition matrix. These matrices are time-variant if the system and/or measurement equations are nonlinear and they may be obtained by linearizing e and $g$in the equations both (1) and (2) every time step cantered on the last estimate, producing the Extended Kalman Filter (EKF). By methodically lowering noise, the Kalman filter was used to greatly improve the reliability of mental health-based emotion identification data. It compensated for measuring errors by accurately estimating the underlying emotional states by employing predictive and corrective methods. Over time, this method enabled more thorough assessments of emotional dynamics and increased the dependability of emotion recognition systems. The Kalman filter allowed for more precise insights into mental health states from intricate and changeable data sources by successfully minimizing noise.

3.3 Recognize the mental health-related emotions of students' education NG-DMCNN

The integration of specialized convolutional neural network architecture, inspired by the Northern Goshawk, combines multi-structured data inputs for enhanced emotion recognition in the context of mental health education. This approach improves accuracy in discerning subtle emotional cues but also facilitates personalized interventions and educational strategies based on comprehensive emotional understanding.

3.3.1 Northern goshawk

The northern goshawk approach during hunting has been simulated in the construction of the suggested NGO algorithm to update the population members. The two main activities of a northern goshawk are simulated by this method: (i) locating and attacking prey, and (ii) chasing and fleeing. There are two phases to these behaviors.

3.3.1.1 *Prey identification (exploration)*

During the first part of its hunt, the northern goshawk assaults its target swiftly after choosing it at random. Because the prey is chosen at random inside the search space, this phase gives the NGO more exploring power. The goal of this phase is to find the ideal location by conducting a global search over the search space. At this stage, the northern goshawk's behavior includes selecting and attacking prey. There is a mathematical model for the ideas presented in the first step.

$$O_j = W_l, j = 1,2, \dots, M, l = 1,2, \dots, j-1, j+1, \dots, M, \quad (9)$$

$$w_{j,i}^{new,O1} = \begin{cases} w_{j,i} + q\left(o_{j,i} - Jw_{j,i}\right), E_{O_j} < E_j, \\ w_{j,i} + q\left(w_{j,i} - o_{j,i}\right), E_{O_j} < E_j \end{cases} \quad (10)$$

$$W_j \begin{cases} W_j^{new,O1}, E_j^{new,O1} < E_j \\ W_j, E_j^{new,O1} \geq E_j \end{cases} \quad (11)$$

Where$o_j$is a random natural number in the interval [1, N], $W_j^{new,O1}$ is the new status for the ith proposed solution,$w_{j,}^{new,O1}$ is its ith dimension, $E_j^{new,O1}$ is its value of the objective is based on the function for the first phase of NGO, q is a number in the random interval [0, 1], and random that can be either 1 or 2. Random numbers called parameters are used to produce random NGO behavior in search and update

3.3.1.2 ***Operation chase and escape***

The victim attempts to fly after being attacked by the northern goshawk. Thus, in a process of chase and tail, the northern goshawk is pursuing its victim. Before beginning on the hunt, the northern goshawk can follow its prey in almost any situation because of its incredible speed. By simulating this behavior, the algorithm's capacity for local search inside the search space is strengthened. It is assumed that this hunting is close to an assault point with a radius Q in the suggested NGO method. Depicts the northern goshawk and prey pursuing one other. The ideas presented in the second stage are represented mathematically where ^{,new,O2}isthe most iteration$s$ that may be made, and the iteration counter j indicates the most recent state of the jth proposed solution, the maximum number of iterations and the iteration counter denotes the updated state of the jth suggested solution, $W_{j,}^{new,O2}$ its i^{th} dimension, and $E_j^{new,O2}$its objective function value according to the NGO's second phase.$[1,]$ $M, E_j^{new,O1}$

$$E_{j,i}^{new,O2} = w_{j,i} + Q(2q-1)w_{j,i} \quad (12)$$

$$Q = 0.002\left(1 - \frac{s}{S}\right)$$

$$W_j = \begin{cases} W_{j,i}^{new,O2}, E_j^{new,O2} < E_j \\ W_{j,}, E_j^{new,O2} \geq E_j \end{cases} \quad (13)$$

3.3.2 Multilayer deep learning convolution neural network

The method utilized in this study, which concentrated on mental health education is using facial expression recognition technology to measure students' emotional reactions throughout class. The first stage is to use cutting-edge technology to record facial expressions. Then, a customized Convolutional Neural Network (CNN) model is created with the express purpose of identifying and deciphering the complex emotions exhibited. Construct a CNN structure with several neural network layers. Build a CNN structure with several neural network layers. First, extend the CNN model with additional learning layers. The next step is to decrease error by optimizing the weights of the models through the use of backpropagation and forward pass calculations. Utilizing the trained CNN model, evaluate the degree to which students' emotional states were recognized throughout mental health education classes. The constructed CNN architecture consists of an input layer, a convolutional (C1), a subsampling (S2), a convolutional (C3), subsampling layers (S4), and an output layer. The dimensions of the input layer are set at 20 by 20. Five-by-five convolutional kernels make up convolutional layer C1. Layer S4 subsampling and an output feature mapping convolutional layers into non-overlapping
2x2 sub-regions allow for the extraction of each sub-region's mean value. 5×5 convolutional kernels are used in convolutional layer C3. Students' emotional states are classified at the output layer using a softmax classifier.

3.3.3 NG-DMCNN recognizes students' emotions in mental health education

The NG-DMCNN system is designed to recognize student's emotions in the context of mental health education. By simulating the hunting strategies of the northern Goshawk, the NG-DMCNN performs efficient exploration and exploitation in its search for optimal solution. This algorithm is integrated with the sophisticated multilayer CNN to analyze facial expressions and discern complex emotional states. The CNN model tailored for this purpose includes multilayer for convolution, sub-sampling, and output, enabling it to capture subtle emotional cues. Through the NG-DMCNN approach, educational institutions can give a comprehensive understanding of the student's mental health, facilitating personalized interventions and strategies to enhance emotional well-being and educational outcomes. This innovative combination of biologically inspired algorithms and advanced neural networks inspired a significant advancement in educational technology, particularly in promoting mental health awareness and support. Algorithm 1 represents the Pseudocode for NG-DMCNN.

Algorithm 1: NG-DMCNN

$Start$

$\#\ Dataset\ Collection$

$function\ collect_{dataset}()$:

$participants_{data}\ =\ []$

$for\ each\ participant\ in\ range(300)$:

$physiological_{data}, facial_{data}\ =\ acquire_{data}(participant)$

$participants_{data}.append((\ participants_{data}, facial_{data}))$

$return\ participants_{data}$

$\#\ Data\ Preprocessing\ with\ Kalman\ Filter$

$function\ preprocess_{data}(participants_{data})$:

$preprocessed_{data}\ =\ []$

$for\ physiological_{data}, facial_{data}\ in\ participants_{data}$:

$filtered_{physiological_{data}} =\ apply\_kalman\_filter(physiological_{data})$

$preprocessed_{data}.append((filtered_{physiological_{data}}, facial_{data}))$

$return\ preprocessed_{data}$

$\#\ NG\ Algorithm\ Simulation$

$function\ ng_{algorithm}()$:

$initialize_{ng_{algorithm}}()$

$while\ not\ stopping_{condition}()$:

$for\ each\ solution\ in\ ng_{population}$:

$prey\_identification(solution)\ \ \ \#\ Phase\ 1: Prey\ Identification$

$chase\_and\_escape(solution)\ \ \ \ \#\ Phase\ 2: Chase\ and\ Escape$

$\#\ DMCNN\ Architecture$

$function\ build_{dmcnn_{model}}()$:

$model\ =\ Sequential()$

$model.add(Conv2D(filters = 32, kernel_{size} = (5,5), activation = 'relu', input_{shape} = (20,20,1)))$

$model.add(MaxPooling2D(pool_{size} = (2,2)))$

$model.add(Conv2D(filters = 64, kernel_{size} = (5,5), activation = 'relu'))$

$model.add(MaxPooling2D(pool_{size} = (2,2)))$

$model.add(Flatten())$

$model.add(Dense(units = 128, activation = 'relu'))$

$model.add(Dense(units = num_{classes}, activation = 'softmax'))$

$return\ model$

$\#\ NG - DMCNN\ Training\ Model\ Integration$

$function\ train_{ng_{dmcnn_{model}}}(preprocessed_{data})$:

$function\ train_{ng-dmcnn\_model}\ (preprocessed_{data})$:

$ng_{algorithm}()\ \ \#\ Run\ ng\ algorithm\ to\ optimize\ solutions$

$dmcnn_{model}\ =\ build_{dmcnn_{model}}()$

$X_{train}, y_{train}\ =\ prepare_{training_{data}}(preprocessed_{data})$

$dmcnn_{model}.compile(optimizer = 'adam', loss = 'categorical_{crossentropy}', metrics = ['accuracy'])$

$dmcnn_{model}.fit(\ X_{train}, y_{train}, epochs = epochs, batch_{size} = batch_{size}, validation_{split} = 0.2)$

$return\ dmcnn_{model}$

$Evaluate\ final\ NG - DMCNN\ model\ performance\ on\ test\ data$

END

4 Result

In this section we have analysed the proposed approach NG-DMCNN performance, and comparative analysis of Bayesian graph convolutional network (BGCN), logistic regression (LR), and support vector machines (SVM).

3.1 NG-DMCNN performance analysis

In this section, we analysed the proposed approach NG-DMCNN performance of emotion recognition. Table 2 and figure 2 represents the various emotions recognitions performance. The ability of an emotion recognition system to categorize emotions like happy, sad, angry, scared, and excited is measured, and the results are displayed in this table. The system does a good job of identifying positive emotional states, as seen by its high accuracy of 97.3% when identifying happy feelings. It does, however, perform less well when it comes to identifying the negative emotional states of sadness (65.9%) and anger (77.8%), where precision and recall levels are significantly lower, indicating difficulties achieving effectively.

Table 2: Performance of emotion recognition

Emotions	Accuracy (%)	Precision (%)	Recall (%)
Happy	97.3	95.9	96.9
Sad	65.9	63.2	71.8
Angry	77.8	73.9	61.8
Scared	82.5	80.2	78.2
Excitement	89.2	85.3	82.2

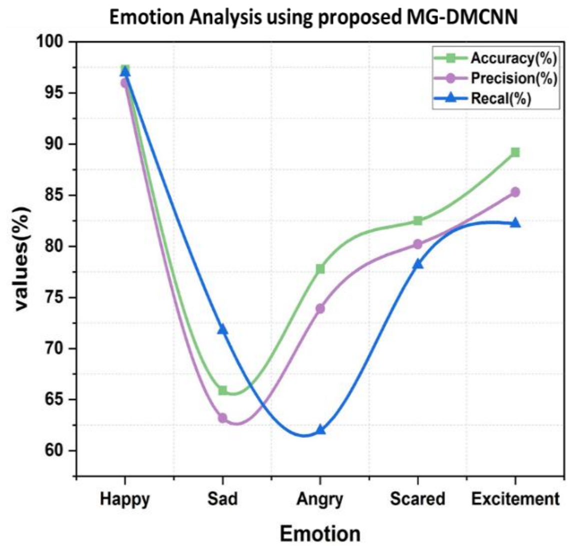

Figure 2: Emotion recognition performance

4.2 Comparative analysis

The Tensor Flow/Keras or scikit learn technique was utilized in this article, along with Python 3.10.1 software, to simulate a Windows 10 laptop with an Intel i7 core CPU and 8GB of RAM. Currently used techniques include Bayesian graph convolutional network (BGCN), logistic regression (LR), and support vector machines (SVM) [22], used for acknowledging the emotions of students in mental health education.

Correct implementation of mental health education allows for the identification of students' unique emotional states, enabling the provision of individualized support and intervention that boosts the effectiveness of educational initiatives. Figure 3 and Table 3 display the precision performance. The proposed NG-DMCNN precision value is 92.38%, outperforming the existing systems, LR, SVM, and BGCN which have the precision of 61.25%, 82.15%, and 89.13% respectively. Our proposed method is effective in students' emotions related to mental health education.

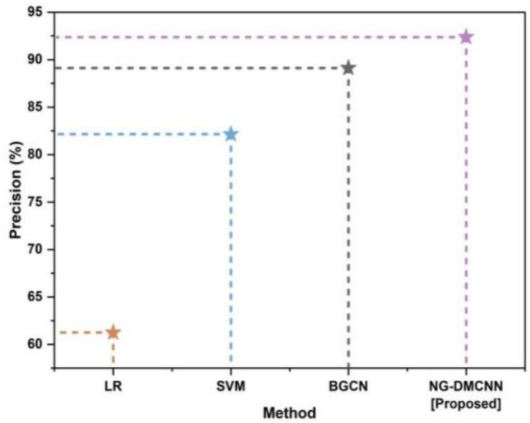

Figure 3: Precision performances

In mental health education, students' emotions frequently exhibit a range, from openness and inquiry to discomfort or anxiety. When these emotions are acknowledged, an optimal setting environment for growth and learning is produced. Figure 4 and Table 3 display the recall performance. The proposed NG-DMCNN recall value is 78.42% which outperforms existing systems, LR, SVM, and BGCN which have recall of 55.90%, 45.26%, and 64.72% respectively. Our suggested method is better than existing methods in students' emotions related to mental health education.

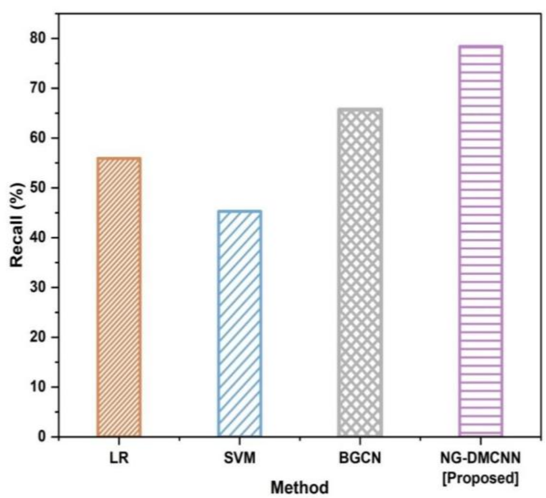

Figure 4: Recall performances

Emotional intelligence in mental health education is essential for accurately adjusting treatments and support to students' needs and promoting their overall health and academic achievement. Figure 5 and Table 3 display the accuracy performance. The proposed NG-DMCNN accuracy value is 94.56% which is outperforming the existing systems, LR, SVM, and BGCN which have an accuracy of 75.91%, 88.67 %, and 90.47% respectively. Our recommended method is superior to existing methods in students' emotions related to mental health education.

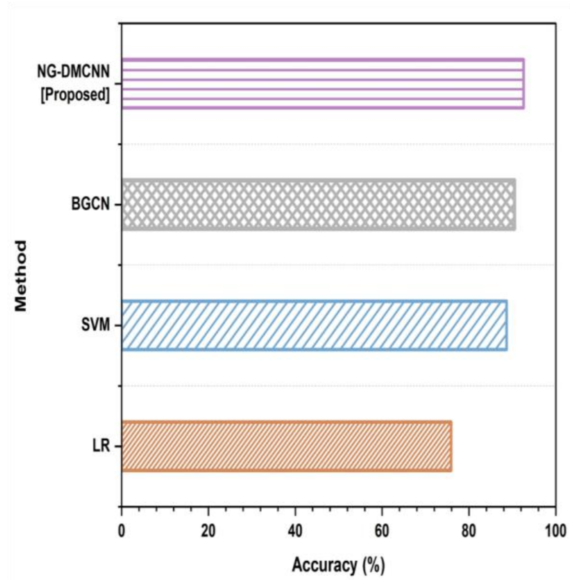

Figure 5: Accuracy performances

A balanced assessment that captures both accuracy and recalls both essential for precisely assessing students' needs and progress is ensured when the emotional reactions of students in mental health education are measured with a high F1 score. Figure 6 and Table 3 display the recall performance. The proposed NG-DMCNN F1 score value is 89.67% outperforming the existing systems, LR, SVM, and BGCN which have an accuracy of 76.44%, 79.56%, and 82.35% respectively. Our recommended method is better than conventional methods in students' emotions related to mental health education.

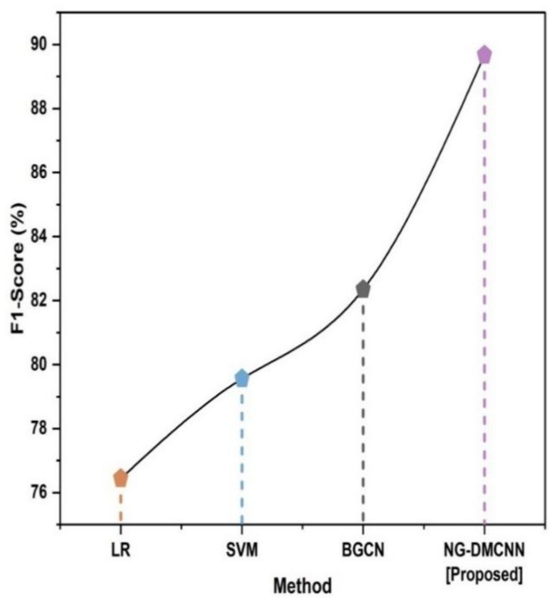

Figure 6: F1 score performances

Table 3: Outcome Values of accuracy, recall, precision, and score.

Methods	Accuracy (%)	Precision (%)	Recall (%)	F1Socre (%)
LR	75.91	61.25	55.90	76.44
SVM	88.67	82.15	45.26	79.56
BGCN	90.47	89.13	64.72	82.35
NG-DMCNN [proposed]	94.56	92.38	78.42	89.67

4.3 Discussion

To create a facial expression analysis system for mental health care that is easy to use, affordable, and efficient in [11]. The technique involves processing face photos and interpreting emotional changes using an LDA classifier and deep features taken from the Fully Connected Layer 6 of AlexNet. It was evaluated on particular databases and could not be applied to all real-world cases, despite the fact that it shows higher accuracy and efficiency. To identify humour, melancholy, and neutral emotions from physiological data to create a methodology for wearable device emotion recognition shown in [12]. Using video clips to induce emotions in 37 participants, the method records galvanic skin reaction and photoplethysmography. Features are then extracted, selection is made using random forest recursive feature removal, and SVM classification is performed in 90% accuracy. The implementation of the NG-DMCNN could assist get over these limitations. By utilizing a more thorough and organized approach to deep learning, this technique can improve the system's performance by potentially improving generalizability across a variety of real-world scenarios and capturing a wider range of human emotions than the small set used in the previous studies. This proposed method findings highlight the efficiency of this approach NG-DMCNN precision (92.38%) in identifying and monitoring participants' emotional conditions, overtaking additional recognised systems identical BGCN (89.13%), SVM (82.15% precision), and LR (61.25% precision). In accumulation to outperforming present techniques, this novel approach collections a new standard for emotion recognition in informative psychology.

5 Conclusion

To define students' excitements about mental health education, we generated a novel NG-DMCNN. By Kalman filtering for noise reduction, the NG-DMCNN was intelligent to accomplishsignificant performance metrics by assessing facial and physiological data from 300 entities. These metrics were accuracy (94.56%), precision (92.38%), recall (78.42%), and F1-score (89.67%). These resultshighpoint the efficiency of this method in identifying and regulatorycontributors'expressive states, overtaking more recognisedmethods like BGCN (89.13%), SVM (82.15% precision), and LR (61.25% precision).When it originates to mental health education, our proposed technique is greater than students' feelings. The measure and demographic diversity of the collection, the condition for real-time dispensation, and ethical reflections all pose limits. Larger, more varied samples, a wider range of feelings to be recognised, real-time submission optimization, and privacy worries should be the main topics of future investigation. The results have applied inferences for data-driven instructive policies, expressivelyapproachable curriculum progress, and developed teacher training, ongoing mental health nursing, and customisededucationinvolvements. In real-world settings, these approach can significantlyimprove educational results and mental health provision. Educational institutions can build more approachable and caring settings that speech the emotional and emotional needs of students by usingprogressivefeelingcreditknowledge. This will eventually lead to enhanced mental health and educationalpresentation for students.

Acknowledgment

1.The research and practice of the integration of "Heart education" and "Five education" in higher vocational colleges under the perspective of the 14th Five-year Plan project of educational Science in Shanxi ProvinceNumber: GH-230077

2.Teaching reform and Practice Research project of Shanxi Provincial Education Department--Research on the practice of "going out" international talent training in vocational education Number: 202303008

Reference

[1] Coventry, P.A., Meader, N., Melton, H., Temple, M., Dale, H., Wright, K., Cloitre, M., Karatzias, T., Bisson, J., Roberts, N.P. and Brown, J.V., 2020. Psychological and pharmacological interventions for posttraumatic stress disorder and co-morbid mental health problems following complex traumatic events: Systematic review and component network meta-analysis. *PLoS medicine*, *17*(8), p.e1003262. https://doi.org/10.1371/journal.pmed.1003262

[2] Wang, W., Xu, K., Niu, H. and Miao, X., 2020. Emotion recognition of students based on facial expressions in online education based on the perspective of computer simulation. *Complexity*, *2020*, pp.1-9. https://doi.org/10.1155/2020/4065207

[3] Drigas, A. and Papoutsi, C., 2020. The Need for Emotional Intelligence Training Education in Critical and Stressful Situations: The Case of Covid-19. *Int. J. Recent Contributions Eng. Sci. IT*, *8*(3), pp.20-36. https://doi.org/10.3991/ijes.v8i3.17235

[4] Shim, Y.R., Eaker, R. and Park, J., 2022. Mental health education, awareness and stigma regarding mental illness among college students. *Journal of Mental Health & Clinical Psychology*, *6*(2), pp.6-15. https://doi.org/10.29245/2578-2959/2022/2.1258

[5] Haidt, J., 2024. *The anxious generation: How the great rewiring of childhood is causing an epidemic of mental illness*. Random House. https://doi.org/10.31234/osf.io/xed6w

[6] Liang, L., Zheng, Y., Ge, Q. and Zhang, F., 2022. Exploration and strategy analysis of mental health education for students in sports majors in the era of artificial intelligence. *Frontiers in Psychology*, *12*, p.762725. https://doi.org/10.3389/fpsyg.2021.762725

[7] Ding, Y., Chen, X., Fu, Q., and Zhong, S., 2020. A depression recognition method for college students using deep integrated support vector algorithm. *IEEE Access*, *8*, pp.75616-75629. https://doi.org/10.1109/access.2020.2987523

[8] Frenzel, A.C., Daniels, L. and Burić, I., 2021. Teacher emotions in the classroom and their implications for students. *Educational Psychologist*, *56*(4), pp.250-264. https://doi.org/10.1080/00461520.2021.1985501

[9] Kolenik, T. and Gams, M., 2021. Persuasive technology for mental health: One step closer to (Mental health care) equality? *IEEE Technology and Society Magazine*, *40*(1), pp.80-86. https://doi.org/10.1109/mts.2021.3056288

[10] Kolenik, T., 2022. Methods in digital mental health: smartphone-based assessment and intervention for stress, anxiety, and depression. In *Integrating Artificial Intelligence and IoT for Advanced Health Informatics: AI in the Healthcare Sector* (pp. 105-128). Cham: Springer International Publishing. https://doi.org/10.1007/978-3-030-91181-2_7

[11] Fei, Z., Yang, E., Li, D.D.U., Butler, S., Ijomah, W., Li, X. and Zhou, H., 2020. Deep convolution network-based emotion analysis towards mental health care. *Neurocomputing*, *388*, pp.212-227. https://doi.org/10.1016/j.neucom.2020.01.034

[12] Domínguez-Jiménez, J.A., Campo-Landines, K.C., Martínez-Santos, J.C., Delahoz, E.J. and Contreras-Ortiz, S.H., 2020. A machine learning model for emotion recognition from physiological signals. *Biomedical signal processing and control*, *55*, p.101646. https://doi.org/10.1016/j.bspc.2019.101646

[13] Ayata, D., Yaslan, Y. and Kamasak, M.E., 2020. Emotion recognition from multimodal physiological signals for emotion-aware healthcare systems. *Journal of Medical and Biological Engineering*, *40*, pp.149-157. https://doi.org/10.1007/s40846-019-00505-7

[14] Tonguç, G. and Ozkara, B.O., 2020. Automatic recognition of student emotions from facial expressions during a lecture. *Computers & Education*, *148*, p.103797. https://doi.org/10.1016/j.compedu.2019.103797

[15] Happell, B., Warner, T., Waks, S., O'Donovan, A., Manning, F., Doody, R., Greaney, S., Goodwin, J., Hals, E., Griffin, M. and Scholz, B., 2022. Something special, something unique: Perspectives of experts by experience in mental health nursing education on their contribution. *Journal of Psychiatric and Mental Health Nursing*, *29*(2), pp.346-358. https://doi.org/10.1111/jpm.12773

[16] Lindow, J.C., Hughes, J.L., South, C., Minhajuddin, A., Gutierrez, L., Bannister, E., Trivedi, M.H. and Byerly, M.J., 2020. The youth is aware of mental health intervention: impact on help-seeking, mental health knowledge, and stigma in US adolescents. *Journal of*

Adolescent Health, *67*(1), pp.101-107. https://doi.org/10.1016/j.jadohealth.2020.01.006

[17] Ahmed, U., Mukhiya, S.K., Srivastava, G., Lamo, Y. and Lin, J.C.W., 2021. Attention-based deep entropy active learning using a lexical algorithm for mental health treatment. *Frontiers in Psychology*, 12, p.642347. https://doi.org/10.3389/fpsyg.2021.642347

[18] Bae, Y.J., Shim, M. and Lee, W.H., 2021. Schizophrenia detection using machine learning approach from social media content. *Sensors*, *21*(17), p.5924. https://doi.org/10.3390/s21175924

[19] Hoffmann, J.D., Brackett, M.A., Bailey, C.S. and Willner, C.J., 2020. Teaching emotion regulation in schools: Translating research into practice with the RULER approach to social and emotional learning. *Emotion*, *20*(1), p.105. https://doi.org/10.1037/emo0000649

[20] Li, L., Gow, A.D.I. and Zhou, J., 2020. The role of positive emotions in education: A neuroscience perspective. *Mind, Brain, and Education*, *14*(3), pp.220-234. https://doi.org/10.1111/mbe.12244

[21] Camangian, P. and Cariaga, S., 2022. Social and emotional learning is hegemonic miseducation: Students deserve humanization instead. *Race Ethnicity and Education*, *25*(7), pp.901-921. https://doi.org/10.1080/13613324.2020.1798374

[22] Dekker, I., De Jong, E.M., Schippers, M.C., De Bruijn-Smolders, M., Alexiou, A. and Giesbers, B., 2020. Optimizing students' mental health and academic performance: AI-enhanced life crafting. *Frontiers in Psychology*, *11*, p.1063. https://doi.org/10.3389/fpsyg.2020.01063

[23] Valiente, C., Swanson, J., DeLay, D., Fraser, A.M. and Parker, J.H., 2020. Emotion-related socialization in the classroom: Considering the roles of teachers, peers, and the classroom context. *Developmental psychology*, *56*(3), p.578. https://doi.org/10.1037/dev0000863

[24] Ding, Y. and Wang, T., 2022. Mental Health Management of English Teachers in English Teaching under the COVID-19 Era. *Frontiers in Psychology*, *13*, p.916886. https://doi.org/10.3389/fpsyg.2022.916886