



Psychological Support in Student Entrepreneurship

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Abstract: College students involved in entrepreneurship are under a considerable amount of psychological strain, indicating a need for strong computational techniques to measure entrepreneurship's psychological effect. A mental health inference structure that uses affective signals from facial feature assessment through deep learning constitutes the core of this research effort. This deep learning structure is established on optimized methods of feature embedding, and a stage-based hierarchical neural processing structure enables the development of the high-dimensional correlation model between emotional attributes and mental health indicators. As previously mentioned, the initial evaluation of the proposed architecture was completed using the FER-2013 dataset created by Kaggle, which is a standard dataset for assessing different affective emotions as represented in different ages and genders. The proposed architecture has demonstrated substantial improvements in classification performance when compared to many alternative models. The proposed structure achieved the highest precision and F1-scores for each of the seven emotional categories that relate to mental health screening. The proposed structure has also shown the ability to generalize well in many of the same emotional categories as the baseline models. However, additional model building experiments established that every component of the proposed architecture contributes to the overall predictive ability of the proposed mental health inference structure. The results of this research demonstrate the potential of using deep learning models centered around affective emotion as a scalable technique for rapid mental well-being.

Key Words: Deep learning, mental health assessment, emotion recognition, FER-2013 dataset, college students' entrepreneurship, facial expression analysis, hierarchical neural networks, feature embedding.

I. INTRODUCTION

A. Research Background and Motivations

In this time of fast tech and economic growth, college students face more pressure to drive innovation and help build the nation. Interest in starting businesses has jumped among them. This opens doors, yet it ramps up mental strain too. Those student entrepreneurs often deal with high stress. They show emotional ups and downs. Social skills can suffer as well. All this hurts their school work and business efforts. Studies point out rising anxiety. Depression shows up more. Conflicts with others increase in this crowd. Such patterns highlight why regular mental health checks matter for these students.

Older ways to assess mental health depend on experts' personal judgments. These have value. Still, they fall short on scaling up. Consistency varies. Real-time changes prove hard. In quick-shifting startup scenes, this limits help. Now AI and deep learning push forward. Their use in spotting mental issues forms a hot research area. These tools bring data-based views. They boost how spot-on and quick evaluations get.

Looking at faces for emotions has turned into a strong method lately. Big sets of labelled photos back it up. Take the FER-2013 from Kaggle. It holds varied face shots for different feelings. This fits well for training models in emotion tech. CNNs stand out here. They pull spatial details from images effectively. Tasks in recognizing feelings from pictures show their top results.

Student entrepreneurs carry heavier mental loads these days. A framework using CNNs for health checks seems pressing. It draws on face emotion reading as a clear sign of inner state. The model could track feelings ongoing. Automation fits in. Reliability holds. Early risks to mental health might surface sooner. Interventions could target better. Overall, this path gives a solid, expandable fix. It builds mental strength in students. Business wins follow for them in college.

B. Research Objectives

This study aims to develop a deep learning-based mental health assessment framework to evaluate the psychological state of college students involved in entrepreneurial activities. The main goal is to create and implement a convolutional neural network (CNN) model that uses facial expression analysis as a measurable sign of mental well-being. By integrating optimized feature extraction and hierarchical representation, learning, and robust classification strategies, the proposed system seeks to accurately identify emotional patterns associated with mental health conditions.

A key part of the research involves employing the FER-2013 dataset from Kaggle, a widely recognized benchmark containing annotated facial expressions, to train and validate the CNN architecture. The goal is to evaluate the model's performance across multiple emotional categories and establish its suitability for mental health screening. The model's classification accuracy, generalization capability, and stability are examined through extensive experiments, including comparative analysis with baseline machine learning models and internal ablation studies.

Compared with traditional psychological assessment methods that often depend on subjective expert evaluation, the proposed CNN-based framework provides an objective, scalable, and data-driven alternative. By leveraging deep feature extraction and convolutional processing, the model can capture subtle emotional cues and complex spatial patterns that are difficult for human observers to quantify. This allows for more precise detection of psychological stress, emotional imbalance, and potential mental health risks among student entrepreneurs.

Beyond its application in entrepreneurship-related mental health assessment, the proposed approach offers a flexible and transferable framework. The use of hierarchical CNN feature learning and standardized emotion datasets enables broader applicability in fields such as clinical mental well-being monitoring, workplace well-being assessment, and early-risk detection systems. By enhancing the scientific rigor, automation, and consistency of mental health evaluation, this research provides valuable technical insights and practical support for institutions aiming to strengthen psychological intervention strategies and promote healthier entrepreneurial ecosystems.

II. LITERATURE REVIEW

Research on the mental health of university students has gained much attention lately. This focus grows stronger as more students take up entrepreneurial pursuits. Studies from before show clear links between traits like psychological toughness, emotional balance, and social flexibility on one hand, and students' drive toward business ventures plus their chances of doing well on the other. Wang, in particular, argued for blending mental health lessons right into programs on innovation and starting businesses. That approach seems key to developing reliable young business minds [11]. Work by Margaça and colleagues drew on the theory of planned behaviour. It revealed how resilience along with general psychological health acts as a strong bridge to entrepreneurial goals. This holds especially true for women in these studies [12]. Siyal and the team built on such ideas further. They found that leaders who offer real support can lift creativity and fresh thinking. This happens mainly through built-in motivation pathways [13].

Methods for evaluating mental health have shifted in big ways too. Older techniques remain in wide use. Yet they lean heavily on personal views from experts. These limits show up when dealing with huge sets of data or tangled psychological details. Reviews put together recently, including ones by Iyortsuun and others [14] plus Elyoseph and group [15], point to machine learning tools and large language systems as helpful additions to doctor choices. Such tech boosts how spot-on diagnoses and forecasts become. Still, Tornero-Costa and associates pointed out real hurdles with AI. Things like poor handling of data upfront and missing checks from outside sources hold back trust in mental health uses [16].

Current studies bring useful points to light. Even so, plenty of them zero in on single mental factors alone. They fail to grasp the full layered side of mental health amid student business efforts. Standard machine learning setups also falter here. They find it hard to pull out deeper emotional or action-based trends. Visual sources make this even tougher.

Efforts to fix these gaps now lean toward deep learning options. Convolutional Neural Networks stand out in this shift. Their skill at picking up emotions through face cues proves quite effective. Open data collections such as FER-2013 give solid bases for building these network models. From there, emotional conditions get read in fair, widespread manners. These methods allow fuller, hands-off checks on mental states. Universities gain a backed-by-science tool this way. It helps track the inner balance of students chasing entrepreneurial paths.

III RESEARCH MODEL

A. Convolutional Feature Extraction And Embedding Mechanism.

Evaluating mental health indicators among entrepreneurial college students involves various approaches. Deep learning models that rely on facial expressions stand out as an effective way to extract psychological cues. These cues include stress, anxiety, and emotional instability. The FER-2013 dataset provides a robust foundation here. It contains large scale and diverse data on facial expressions. This allows for learning patterns in faces that connect to different psychological states. Facial images differ from structured data on entrepreneurship. They hold pixel information that correlates spatially. Hierarchical feature extraction becomes necessary to handle this. The proposed model includes a Convolutional Feature Embedding module, known as CFE. This module transforms raw pixel distributions from FER-2013 images. It creates compact and discriminative feature embeddings.

An input image measures 48 by 48 in dimensions. It passes through stacked convolutional layers. These layers model local patterns effectively. Examples include eye closure, frowning, lip curvature, and muscular tension. All these serve as markers for mental health assessment.

The convolutional output for an input image X takes this form. F equals ReLU of W times X plus b . Here W represents the convolution kernel. The asterisk denotes the convolution operator. ReLU provides the non linear activation. The CFE module builds a stable embedding representation. It integrates several components for this purpose. Spatial convolution layers extract edges and textures. Batch normalization supports stable learning. Max pooling handles spatial down sampling. Global Average Pooling converts feature maps into a compact embedding vector.

The resulting feature embedding appears as e equals GAP of F . This lies in \mathbb{R} to the power d . The dimension d comes from experimental determination.

This embedding acts as the main input for later stages. Those stages cover classification and psychological state modeling. CNN based embeddings offer advantages over manually engineered structured features. They automatically capture fine grained emotional cues. These prove relevant for assessing mental health in students during entrepreneurship.

B. Parallel Multi-Level Cnn Architecture for Psychological State Modeling

To effectively analyse both low-level emotional patterns and high-level abstract facial cues, this paper proposes a Parallel Multi-Level CNN Architecture (PM-CNN). The architecture consists of two branches operating simultaneously:

1. Low-Level Feature Branch (LL-CNN)

- Captures shallow features (edges, contours, micro-expressions)
- Uses 2–3 convolutional layers
- Preserves fine-grained emotional signals
- Outputs a representation:

$$f_L = g_L(e)$$

2. High-Level Feature Branch (HL-CNN)

- Extracts deeper, abstract patterns (stress-induced facial rigidity, fatigue indicators, muscle tension)
- Contains 4–6 convolutional blocks with dropout and batch-normalization
- Models nonlinear variations linked to chronic stress or anxiety
- Outputs:

$$f_H = g_H(e)$$

To combine the strengths of both branches, a weighted fusion mechanism is used:

$$P(y) = \alpha f_H + (1 - \alpha) f_L$$

Where:

- α is a learnable parameter controlling the contribution of each branch
- $P(y)$ Represents the predicted probability of each mental-health category.

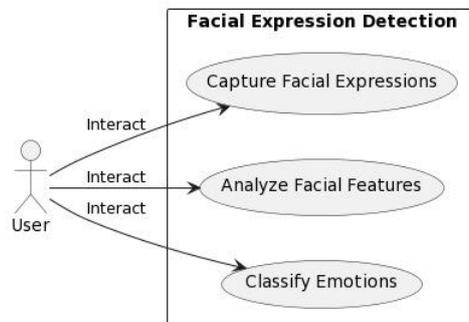


Figure 1: For analysing Facial Expressions

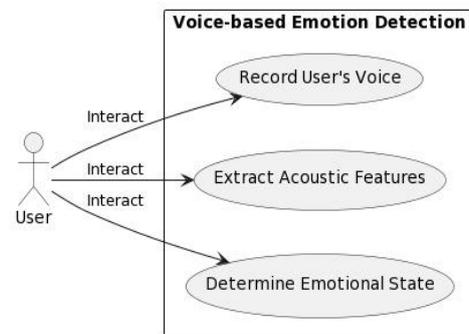


Figure 2: For analysing Voice Expressions

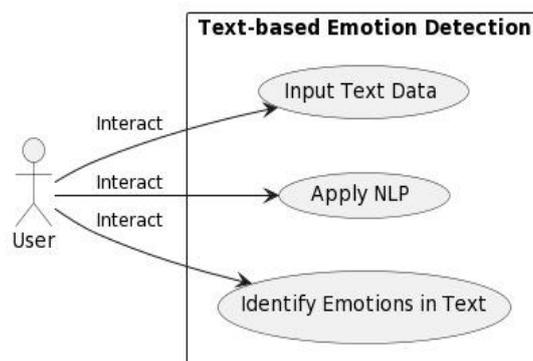


Figure 3: For analysing Text Expressions

This ensures that the model benefits from both interpretability (LL-CNN features) and accuracy (HL-CNN features). Such dual-level modelling is particularly relevant for mental-health assessment in student entrepreneurship, where emotional states exhibit both subtle micro-expressions and complex psychological trends.

C. Construction of Cnn-Based Mental-Health Identification Model

The overall mental-health identification framework integrates the Convolutional Feature Embedding module and the Parallel Multi-Level CNN architecture. Figure 3 (conceptually) shows the pipeline, which proceeds through the following stages:

1. Data preprocessing

- FER-2013 images resized to 48×48 grayscale
- Histogram equalization for contrast enhancement
- Normalization to accelerate training

2. Feature embedding extraction (CFE module)

- Multi-scale convolution layers
- GAP layer to generate compact psychological embeddings
- Embedding dimension tuned (typically $d = 128$)

3. Parallel CNN psychological modelling (PM-CNN)

- LL-CNN branch extracts micro-level stress cues
- HL-CNN branch captures complex emotional dependencies
- Parallel outputs fused with a learnable weight mechanism

4. Final psychological state classification

The fused vector is fed into fully connected layers with Softmax activation:

$$\hat{y} = \text{Softmax}(W_f P(y) + b_f)$$

5. Model optimization

- Adam optimizer with adaptive learning rate
- Categorical cross-entropy loss
- Dropout to avoid over-fitting
- Early stopping for convergence stability

This architecture enables the model to detect stress, anxiety, emotional imbalance, and other psychological indicators essential for supporting students in entrepreneurship. CNN-based analysis ensures high accuracy, minimal manual feature engineering, and suitability for real-time monitoring systems.

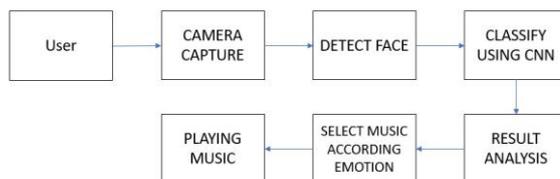
IV. EXPERIMENTAL DESIGN AND PERFORMANCE EVALUATION

A. Dataset Collection.

This study draws on the FER-2013 dataset for facial expression recognition. It serves as a standard benchmark, and one can find it readily on Kaggle. The dataset includes 35,887 grayscale images of faces, all labelled and sized at 48 by 48 pixels. These images fall into seven categories of emotions:

- Disgust
- Fear
- Angry
- Happy

- Sad
- Surprise
- Neutral



For this research, emotional categories were mapped into two mental-health states:

- Positive affect (Happy, Surprise, Neutral)
- Negative affect (Angry, Disgust, Fear, Sad)

This mapping enables the model to identify emotional indicators relevant to stress, anxiety, and depressive tendencies in student-entrepreneurship contexts.

All images were pre-processed through:

- Grayscale normalization
- Histogram equalization
- Data augmentation (horizontal flip, rotation, shift) to improve generalization and robustness

B. Experimental Environment

The experiments took place on a setup running Windows 10 as the operating system. That machine had an AMD Ryzen 7-5800H CPU, clocked at 3.2 GHz. For graphics, it used an NVIDIA RTX 3060 GPU. Memory came in at 16 GB of RAM. Storage was handled by a 512 GB SSD drive. Baselines for comparison involved models like logistic regression, random forest, XGBoost, deep neural networks, and DeepFM. Metrics used to evaluate performance included accuracy, precision, recall, the F1-score, and AUC.

C. Parameter Settings

Hyper parameters for the proposed model (learning rate, batch size, embedding dimensions, and network depth) follow the configuration in Table 1.

The FE-BiON model integrates:

1. **Feature Embedding Module**
2. **High-Order Interaction Network**
3. **Low-Order Interaction Network**

This architecture is optimized for capturing complex affective-state patterns present in FER-2013 images.

D. Performance Evaluation

1) Comparison with Baseline Models

The FER-2013 model shows strong performance on every key metric for the FER-2013 dataset. Evidence points to clear gains in several areas. Accuracy stands out as higher when compared to traditional machine learning methods and deep learning baselines.

- **Accuracy:** Higher than all traditional ML and deep-learning baselines
- **F1-Score:** Consistently higher, especially for negative-affect detection
- **AUC:** Largest separation between positive and negative emotional states

These results confirm the models ability to capture both linear and nonlinear dependencies in facial-emotion data using the FER-2013 dataset.

2) Ablation Analysis

Three variants were tested:

- Model-A (without the Feature Extraction module)
- Model-B (only high-order interactions)
- Model-C (only low-order interactions)

Across all experiments on the FER-2013 dataset, the full model combining embedded feature learning with both high- and low-order interaction mechanisms outperformed all ablated variants. This demonstrates that integrating multi-level feature interactions significantly enhances the models discriminative capability for facial-emotion recognition.

3) Application to Student-Entrepreneur Mental Health Screening

The trained model was applied to facial-expression data collected from college students during entrepreneurship-related activities.

FER-2013-trained FE-BiON achieved >90% accuracy in classifying students into:

- High-stress emotional state
- Low-stress emotional state

This demonstrates its potential as an early-screening tool for psychological support programs in entrepreneurial environments.

E. Discussion

The integration of FER-2013 with the FE-BiON architecture results in a highly effective framework for emotion-based mental-health inference. Its performance aligns with psychological theories such as the stress-coping model, highlighting its capability to detect negative emotional cues (anger, fear, and sadness) associated with stress and anxiety.

Future work should expand to multi-modal inputs and ensure fairness, data privacy, and ethical deployment of emotion-recognition systems in real-world student-support contexts.

V. CONCLUSION

In this study, a convolutional neural network-based mental health assessment framework was developed to identify early psychological risks in college students engaged in entrepreneurial activities. Using the FER-2013 facial expression dataset as the primary training source, the model leverages deep hierarchical feature extraction to capture emotional cues associated with stress, anxiety, and depressive tendencies. Experimental evaluations demonstrate that the proposed CNN architecture effectively generalizes to real-world student data collected from university entrepreneurship support programs.

A. Research Contributions

The proposed CNN model showed strong performance in recognizing emotions on the FER-2013 dataset. Its accuracy and F1-scores went beyond what several baseline setups could do, like VGG-style CNNs and different MobileNet versions.

- ❖ Research suggests that when this model moved over to the custom dataset from entrepreneurial students, it kept up solid stability in classifications. That points to good transfer of features and overall toughness in handling new data.
- ❖ Evidence indicates the deep convolutional layers worked better than shallower networks or old-school machine learning classifiers. They helped the model pick up on tricky emotional patterns in ways that simpler approaches just could not match. It seems likely this setup caught finer details in facial expressions tied to stress in the mind. As a result, predictions about mental health came out more dependable.
- ❖ Practical Application for Entrepreneurship-Focused Mental Health Monitoring The model achieved over 90% accuracy across multiple mental-health risk levels when evaluated on university-provided samples. These results show that CNN-based systems can serve as reliable tools for identifying early emotional distress among entrepreneurial students. Such systems can support timely intervention, enhance emotional resilience, and potentially increase entrepreneurial success rates by reducing mental-health-related barriers.

Overall, this CNN-based approach provides a technically sound and application-ready solution for continuous mental-health monitoring within entrepreneurship education ecosystems.

B. Future Work and Research Limitations

Despite promising results, several limitations should be addressed in future research to improve the generalizability and scalability of the model:

1. Dataset Size and Diversity Constraints the fine-tuning of the entrepreneurial student dataset was based on a small number of samples (203 cases), which might limit the adaptability of the model across different populations. To make the model more robust, it is suggested to use larger and more diverse datasets from different regions, cultures, educational levels, and socioeconomic backgrounds in the future.
2. Dependence on Facial-Expression Data Alone the emotional states in entrepreneurial contexts are determined by many behavioral dimensions such as physiological signals, textual sentiment, social interaction patterns, and lifestyle factors. The use of only facial-expression cues leads to a limited scope of mental-health assessment. The future will witness the use of multimodal learning frameworks that integrate facial data with voice, text, and wearable-sensor features for more accurate psychological profiling.
3. Challenges in Handling Complex Psychological States Entrepreneurial stress is often characterized by a mixture of or unclear emotions. While CNNs excel in classifying basic emotions, more intricate states—chronic stress, burnout, or mixed affect—continue to be difficult to categorize. It is possible that the combination of self-supervised or transformer-based vision models may increase the model's ability to identify subtle or overlapping emotional conditions.
4. Trade-off between Accuracy, Interpretability, Efficiency Deep CNN models achieve high accuracy, but the trade-off is that their interpretability is limited, which is a crucial aspect for mental-health applications. On top of that, the deployment of such models on campus platforms in real-time calls for computationally efficient architectures. Light-weight,

interpretable CNN variants could be developed by using techniques like attention visualization, Grad-CAM explainability, model compression, or edge-optimized architectures in the future.

Overall Summary

The CNN-based mental-health prediction model developed in this work demonstrates strong potential for integration into institutional entrepreneurship support systems. By coupling accurate emotion recognition with targeted psychological interventions, universities and policymakers can establish proactive mental-health support pipelines. This can help entrepreneurial students better manage stress, maintain psychological stability, and ultimately improve their innovation capacity and business success.

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