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Mobile Computer-Assisted Application for Stress Detection Based on Facial Expression Using Modified Convolutional Neural Network

Slamet Riyadi[1], Naufal Rozan[1] and Cahya Damarjati[1]

[1] *Department of Information Technology, Universitas Muhammadiyah Yogyakarta, Yogyakarta, Indonesia*

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Abstract: In this challenging digital era, stress has become an inseparable part of daily life, affecting all ages. Although researchers have discussed stress detection extensively, there are few practical and accessible applications for users. This research aims to develop a mobile application utilizing a modified Convolutional Neural Network (CNN) for stress detection based on facial expression, thereby enabling more effective and efficient stress detection and management. The well-known CNN architectures, i.e., DenseNet201, MobileNetv2, and ResNet50, could have been more optimal for detecting stress from facial expressions. Hence, the CNN architectures are modified to enhance the accuracy of the task by adding dropout layers, Pooling2D, and ReLU Activation. The research was conducted through data collection, image pre-processing, training the model with the modified CNN architectures, and developing a mobile application for stress detection. With the modifications made, this research succeeded in increasing the model's accuracy in detecting stress from facial expressions, where the modified DenseNet201 achieved the highest accuracy, from 75.90% to 77.83%. The mobile application can detect stress based on facial expression image obtained from file or camera. In addition to its primary functionality, the application also provides practical advice to users on managing stress, depending on their detected stress levels. These features aim to enhance user awareness and promote early stress management. In conclusion, using artificial intelligence technology, especially through modifying the CNN architecture, enhances the accuracy of stress detection from facial expressions, and the developed mobile application offers a practical and scalable solution.

Keywords: Convolutional Neural Network (CNN), Stress Detection, Facial Expression, Mobile Application, Architecture Modification

1. INTRODUCTION

In the current digital era, where life moves swiftly and is full of challenges, stress has become an inseparable part of the existence of many people, entering their routine as a situation in which individuals feel pressured or tense [1]. Lazarus and Folkman (1984) define stress as the relationship between the individual and their environment that someone evaluates as taxing or exceeding their resources and endangering their well-being [2]. This confirms that stress has become a common phenomenon, not limited to any specific context like school, work, or family, but is a universal experience affecting all ages, from teenagers to adults [1], [2]. According to [3], the incidence of stress has reached more than 350 million individuals worldwide, making it one of the top health issues globally and highlighting the importance of addressing this issue seriously.

One significant aspect that is often overlooked is the unawareness of many individuals about the stress they are experiencing. Acknowledging the presence of stress is a crucial first step in addressing it, as ignoring it can have serious health consequences, affecting mood, the condition of skeletal muscles, and internal organ functions such as heart failure due to increased heart rate [4], [5], [6]. The deficiency in recognizing the signs of stress adds difficulty in managing it, emphasizing the importance of awareness as a preliminary step in identifying and managing stress before it develops into a larger issue.

Interestingly, stress identification can be observed through the face, where expressions and conditions of the face can reveal the emotional stress someone is experiencing. Features of stress on the face can include signs of tension such as dilated pupils, twitching eyelids, pale skin color, and appearances of being tired or tense [5], [7]. This indicates that the face reflects our emotions and can be a valuable tool in recognizing stress in oneself or others.

Therefore, awareness of stress through facial observation

E-mail address: riyadi@umy.ac.id, naufal.rozan.ft20@mail.umy.ac.id, cahya.damarjati@umy.ac.id

offers an alternative path for detecting and managing stress earlier. This research aims to develop a mobile-based application to detect stress from facial expression images using a modified Convolutional Neural Network (CNN) algorithm. It is hoped that with this technology, individuals can more easily recognize when stress is affecting them, allowing them to take steps to manage it before it adversely impacts their health.

However, detecting stress from facial expressions presents specific challenges. Existing methods may lack accuracy and practicality, making it difficult to implement in everyday scenarios. Therefore, there is a need for improved techniques that can provide reliable and efficient stress detection.

This study aims to develop a mobile application utilizing a modified Convolutional Neural Network (CNN) for stress detection based on facial expression. By modifying the CNN architecture, this research seeks to provide a practical and accessible solution for personal stress detection and management, enabling individuals to identify stress and take preventive measures before it adversely affects their health.

2. RELATED WORK

The increasing reliance on technology has paved the way for various initiatives to integrate practical technology solutions. This research inspires stress detection using smartphones and wearable sensors and aims to explore similar potential in stress detection with different methods [8]. Applications like these offer a quick, economical, and accessible method for early stress detection due to the increasingly sophisticated capabilities of computers. Although many studies have examined stress detection, implementing these findings into mobile applications still needs to be improved. In the last five years, various Deep learning algorithms have been utilized for stress detection, as shown in Table I.

In previous studies specifically addressing stress detection, as noted in Table I, CNN emerged as the most frequently used deep learning algorithm. These studies have tried to identify stress from various aspects and have provided satisfactory results. The widespread use of the CNN model indicates its effectiveness in image analysis, including stress detection through facial analysis. However, most of these studies focus on developing Deep Learning models to achieve optimal performance without considering their practical implementation in mobile applications. This indicates that mobile application development for stress detection requires further research.

However, it is important to note that using the original CNN without modification in stress detection through facial expression faces challenges, including the inability to effectively address the diverse scale, pose, and illumination changes in facial images. Base CNN often requires a large amount of training data to achieve accurate results, making it less ideal for applications with limited or specific datasets.

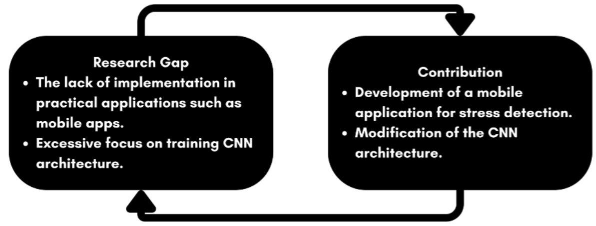

Figure 1. Research Gaps and Proposed Contributions

Furthermore, unmodified CNN architecture might not be fully optimal for extracting the subtle emotional features required for accurate stress detection, as they are designed for more general computer vision tasks rather than detecting complex emotional nuances.

Considering the challenges faced using base CNN, this research is directed towards developing a mobile application as a tool for stress detection through facial expression analysis. Expressions and conditions of the face can be strong indicators of the emotional stress someone is experiencing, underscoring the importance of adjustments and optimization of CNN architecture. This aims to enhance accuracy and efficiency in detecting stress and ensure that the application is practical and easily accessible by users. This literature review comprehensively covers relevant studies on stress detection using facial expressions and CNNs, discussing seminal works, methodologies used, and key findings in detail. It provides a critical analysis of existing methods for stress detection, highlighting their strengths, limitations, and how the proposed approach addresses these limitations.

This research proposes an innovative approach to addressing the challenges of variability in facial expressions, positions, and lighting conditions by integrating advanced image processing and machine learning techniques. With a focus on developing an effective deep learning model and its applicability, the application is designed to be a practical solution that allows easy and efficient stress detection through mobile devices.

Thus, this research aims to address the gap in the literature by presenting a solution through the development of a mobile application. It is expected to significantly contribute to the field of stress detection, offering new insights into the application of machine learning technology to support individuals' mental health and well-being. The existing research gap and the contributions proposed by this research are summarized in Figure 1.

3. METHODS

This research takes step-by-step measures to achieve its goal of developing a stress detection application using facing analysis, divided into four main phases. The first phase involved collecting and pre-processing facial image data, followed by the implementation of the CNN architecture to

TABLE I. Trends In Research Applying Deep Learning algorithm For Stress Detection

Ref	Dataset	Data Type	Methods/Architecture	Result
[9]	Facial Expression Image	Image	Custom MobileNet V2	Acc = 95%
[10]	Psychophysiological Stress Dataset	Psychophysiological Data	1D CNN	Acc = 99.7%
[11]	Facial Expression Image	Image	VGG16	Acc: 92.1%
[12]	Video based	Video	TSDNet	Acc: 85.42%, F1: 85.28%
[13]	PhysioBank	Physiological Signals	Gradient Boost Feature Selection	Acc: 83.33%
[14]	Electroencephalography Signals	Electroencephalography Signals	Majority Voting-based Model (SVM, KNN, Naïve Bayes)	Acc: 93.85%
[15]	Wearable Stress and Affect Detection (WESAD)	Sensor Data	Custom Method	F1-score: 83.34%
[16]	Unknown	Unknown	Deep Learning	Acc: 85.71-97.50%, Loss: 0.4061-1.8144
[17]	Facial Expression Image	Image	Unknown	Unknown
[18]	Audio-Visual Dataset	Video	Custom CNN	Acc: 94.33%
[19]	Data Social Platform	Social Media Data	Custom CNN	Acc: 91.55%
[20]	Unknown	Unknown	Fuzzy Logic based IoT	Accuracy: 92.5%
[21]	Biosignals	Biosignals Data	Stroop Colour-Word Test	Unknown
[22]	Unknown	Heart Rate, Breath Rate, Blood Oxygen, and Stress Level	Systematic Bibliographic Review (SBR)	Unknown
[23]	Jaypee Institute of Information Technology	Student's Data	Support Vector Machine	Acc: 85.71%
[24]	Stress Recognition in Automobile Drivers by Healey and SWELL-KW dataset	Physiological Signals	AdaBoost and Decision Tree	Acc AdaBoost: 66.8%, Acc Decision Tree: 74.8%
[25]	Physiological Signals Dataset	EDA and PPG Signals	Random Forest	Acc: 92%
[26]	Physiological Signals Dataset	EDA, Activity, ST	DNN	Acc: 98.3%
[27]	Food Pedia Dataset	Image Inputs	CNN	Acc: 97%
[28]	Geneva affective picture database	Heart Rate	SVM	Acc Training: 82%, Acc Test: 62%
[29]	Wearable Stress and Affect Detection (WESAD) and VerBIO	EDA Signals	K-nearest neighbors (KNN), Logistic Regression, and Random Forest	Highest Acc: 85.7%
[30]	Physiological Signals of Participants	Physiological Signals	Random Forest	Acc: 97.92%
[31]	Wearable Stress and Affect Detection (WESAD)	EDA Signals	Linear Discriminant Analysis	Acc: 87.4%
[32]	ElectroEncephaloGraphy Dataset	Age, Sex, Cp, Trestbps, Fbs, Restecg, Thalach, Old Peak, Slope, Ca, Thal and Target	Random Forest Classifier, Decision Tree, Naive Bayes, Support Vector Machine, and K-Nearest Neighbor	Acc: 93.2%
[33]	Physiological Signals Dataset	Respiration, GSR Hand, GSR Foot, Heart Rate, and EMG	K-Nearest Neighbor	Acc: 98.41%

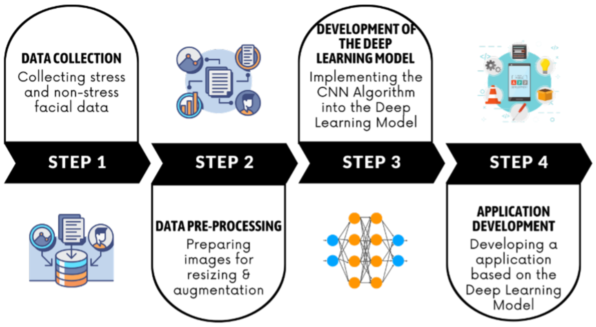

Figure 2. Research Framework for the Development of the Mobile Application for Stress Detection

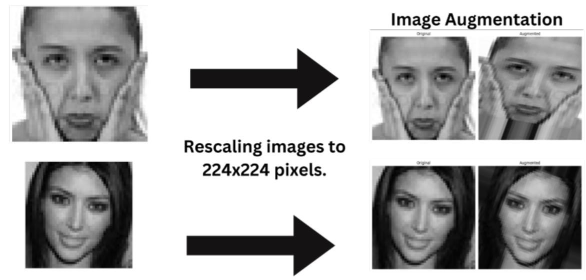

Figure 3. Pre-processing Process

build a Deep Learning model. Lastly, the precess includes the creation of a mobile application that detects stress on the face. Figure 2 below presents a complete description of each phase in this research.

A. Data Collection

Detecting stress through facial expressions require the collecting and categorizing of facial samples into two groups, those showing stress and those not stressed. Indicators such as dilated pupils, twitching eyelids, skin color changes, and expressions of fatigue or tension [5], [7] key to classifying into the stress group.

This research used 12,275 facial images from the Stress Face Dataset [34] sourced from Kaggle. These images were then processed through a pre-processing stage to improve data quality. This step is crucial to ensure that the data is ready for use in developing an accurate deep learning model.

B. Data Pre-processing

After obtaining all the necessary data, the dataset was divided into three parts: training, testing, and validation, with a proportion of 60:20:20. This resulted in a total distribution of 7,347 images for training, 2,448 for validation, and 2,480 for testing.

After dividing the dataset, the research continued improving the quality and quantity of facial images showing stress through the pre-processing stages. A rescaling resolution technique was used to improve quality, making all images the same size, namely 224x224 pixels. The next step, image augmentation, was applied to enrich the dataset with rotation and horizontal flip techniques. The main purpose of this pre-processing is to prepare an optimal dataset for experiments in detecting stress using variations of CNN architecture. Details of the pre-processing process and dataset readiness for further experiments are outlined in Figure 3.

C. Development of the Deep Learning Model

Developing the deep learning model is the next stage of this research to classify stress through facial expressions. In building this model, the research relies on the sophistication of the Convolutional Neural Network (CNN), which is recognized for its effectiveness in image pattern recognition [35]. The model is enriched by applying the latest CNN architectures, such as DenseNet201, MobileNetV2, and ResNet50, known for extracting complex and accurate features [36]. This model is particularly well-suited for detecting stress, as it excels in image analysis, especially in facial recognition. By leveraging these advanced CNN architectures, the model can effectively identify subtle stress indicators in facial expressions, providing a robust tool for stress detection.

Layers such as dropout, Pooling2D, and Relu Activation are integrated to improve reliability and avoid overfitting, as illustrated in Figure 4. Layers such as dropout, Pooling2D, and ReLU activation are integral components of artificial neural network architectures aimed at enhancing reliability and mitigating overfitting. Dropout, for instance, randomly omits a fraction of units within the network during training, diminishing reliance on specific connections and fostering model generalization [37]. Pooling2D diminishes the spatial dimensions of image representations, thereby reducing the number of parameters and computational load within the network, consequently mitigating the risk of overfitting.

Moreover, pooling layers excel in tasks related to image recognition [38]. Meanwhile, ReLU activation introduces non-linearity into the network, enabling the acquisition of more complex representations of input data. Additionally, ReLU activation is renowned for its ability to recognize objects and accurately compare faces [39]. Effectively, click here to enter text. By incorporating these elements into neural network architectures, applications such as stress detection can achieve efficient and accurate performance.

Adding extra layers in the CNN architecture is expected to enhance the ability to extract characteristic features of images related to stress and improve the accuracy level in recognizing stress on the face. By leveraging weights trained on ImageNet, transfer learning techniques also aim to accelerate and maximize the efficiency of the Deep Learning model training process. Subsequently, the developed model is stored in the TensorFlow format, allowing its integration into a mobile application and facilitating the

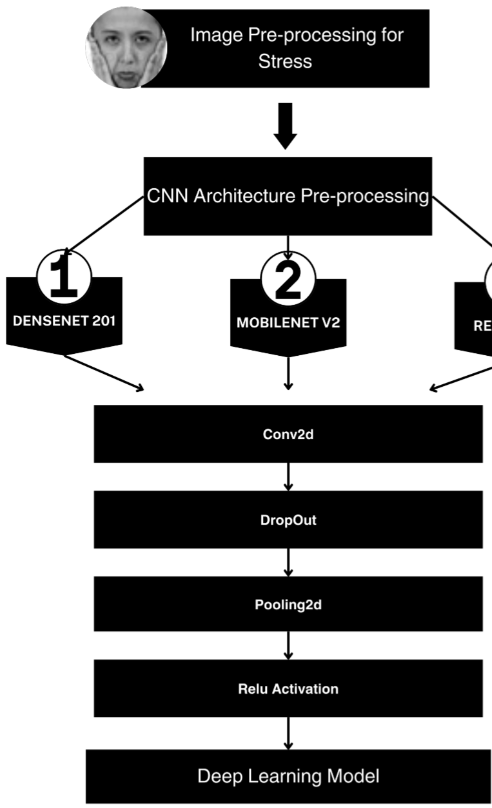

Figure 4. Stages of CNN Modification

practical implementation of this research's findings.

To evaluate the model's performance, accuracy is calculated by comparing the predicted labels against the true labels in the test dataset. This metric provides a quantitative measure of the model's ability to correctly identify stress indicators in facial expressions. Additionally, the performance of the modified CNN architectures is compared with that of their unmodified counterparts. This comparison shows that the modified models achieve higher accuracy, demonstrating the effectiveness of the modifications in enhancing the model's ability to detect stress. This evaluation underscores the improvements brought by the modifications and validates their significance in real-world applications of stress detection.

D. Application Development

The final phase of this research involves creating a mobile application designed to use the previously developed Deep Learning model to detect stress. This application facilitates user access, allowing them to check for stress on themselves through the face, which can be done anywhere and anytime, thereby increasing self-awareness regarding stress conditions. The availability of this application is expected to provide a practical solution to address the lack of individual awareness of the stress they experience. The structure of this application development is further explained in Figure 5.

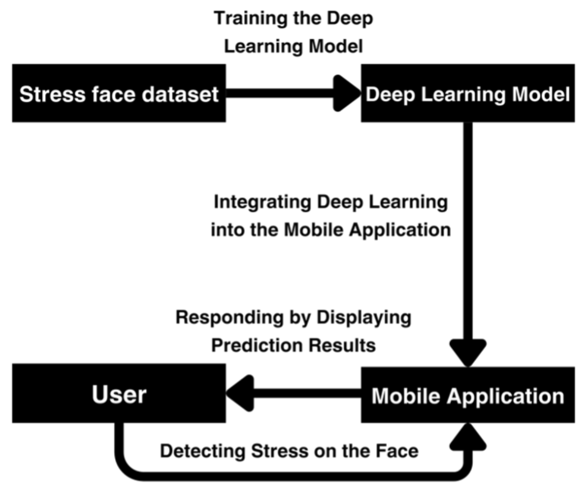

Figure 5. Application Development

Figure 5 illustrates how this research utilizes the Deep Learning model stored in TensorFlow to integrate the model into the mobile stress detector application. TensorFlow is a leading numerical computing framework for deep learning [40]. This research will develop a mobile-based application that allows users to access the previously developed Deep Learning model through a mobile application.

4. RESULT AND DISCUSSION

This section is divided into two main parts, the results of the development and evaluation of the CNN model for stress detection, and the results of the development of a mobile application for personal stress detection. The first part focuses on the performance and effectiveness of the modified CNN architectures in detecting stress from facial expressions. The second part presents the details and functions of the developed mobile application, highlighting its features, blackbox testing, and future work.

A. Modelling Result

This section describes the research results on developing stress detection software that uses a trained modified CNN architecture. The discussion begins with the results from the collection and pre-processing of data. The discussion continues by showing the results of developing the Deep Learning model and how well it functions to detect stress. This research will conclude by presenting the results of the designed application as an alternative method of detecting stress, complete with its features.

This research compares the modified and original CNN architecture against the specially prepared dataset. The main goal is to test whether modifications to the architecture with the addition of layers can improve the ability of the Deep Learning model to detect indications of stress from facial expressions. The research results show that modifications to

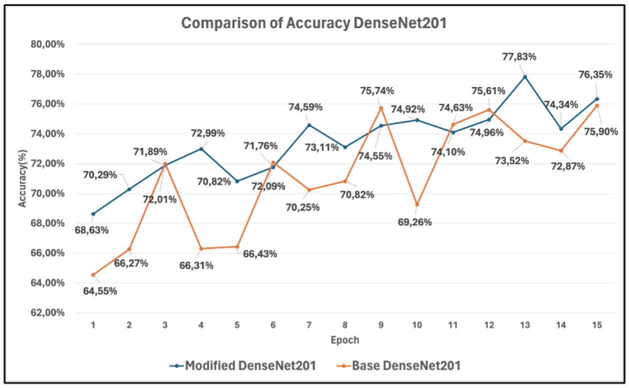

Figure 6. Comparison of DenseNet201 Accuracy

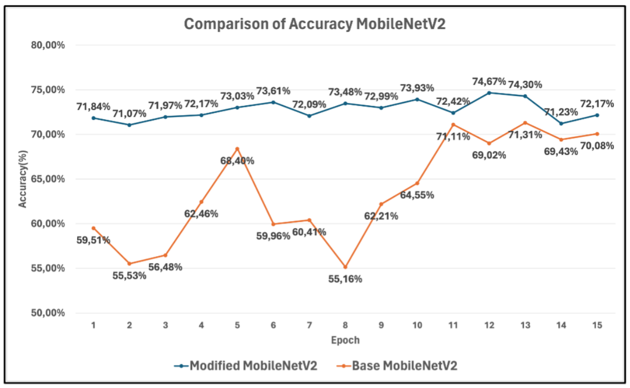

Figure 7. Comparison of MobileNetV2 Accuracy

the CNN structure with extra layer additions successfully improved the efficiency and accuracy of the Deep Learning model in recognizing facial expressions indicating stress.

In this experiment, the modified DenseNet201 architecture was used. As a result, with the modified version, the performance of the Deep Learning model improved, achieving an accuracy rate of 77.83%. This marks an improvement compared to the performance of the base DenseNet201 architecture, which only reached a maximum accuracy of 75.90%. Therefore, modifications to the architecture successfully increased accuracy by 1.93%. For a clearer illustration, a graph comparing the accuracy between the modified version of DenseNet201 and the base DenseNet201 is presented in Figure 6.

Modifications made to one architecture positively impacted other architectures, resulting in an accuracy increase of more than 3% in both architectures. As evidence of this improvement, graphs showing the increase in accuracy for MobileNetV2 and ResNet50 are presented in Figures 7 and 8.

These results confirm that changes to the three architectures have effectively increased the accuracy of Deep Learning. All three architectures showed greater improvements

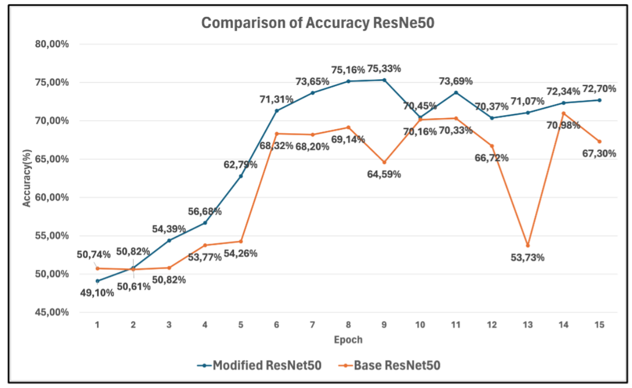

Figure 8. Comparison of ResNet50 Accuracy

Figure 9. Application Features

compared to the architectures without modification. This marks a great success in proposing an alternative method for stress detection through facial analysis.

B. Develop Application

After achieving the optimal model, the stress detector application was developed using TensorFlow. This model was converted into TensorFlow Lite for integration into a mobile application, allowing the model to run quickly and efficiently on mobile devices with low latency. This facilitates the offline use of the application without the need for an external server connection. Figure 9 explains the main features of the developed mobile application, designed to classify facial expressions into two categories: stressed and not stressed.

This application's main and most important feature is the stress detector through the face. This aligns with the application's main goal, making this feature crucial for users in identifying their stress levels. Users can easily upload a photo of their face or use the camera to directly take a picture of their face, which the application will then analyze to determine if there are indications of stress. The accuracy level of this analysis will be displayed on

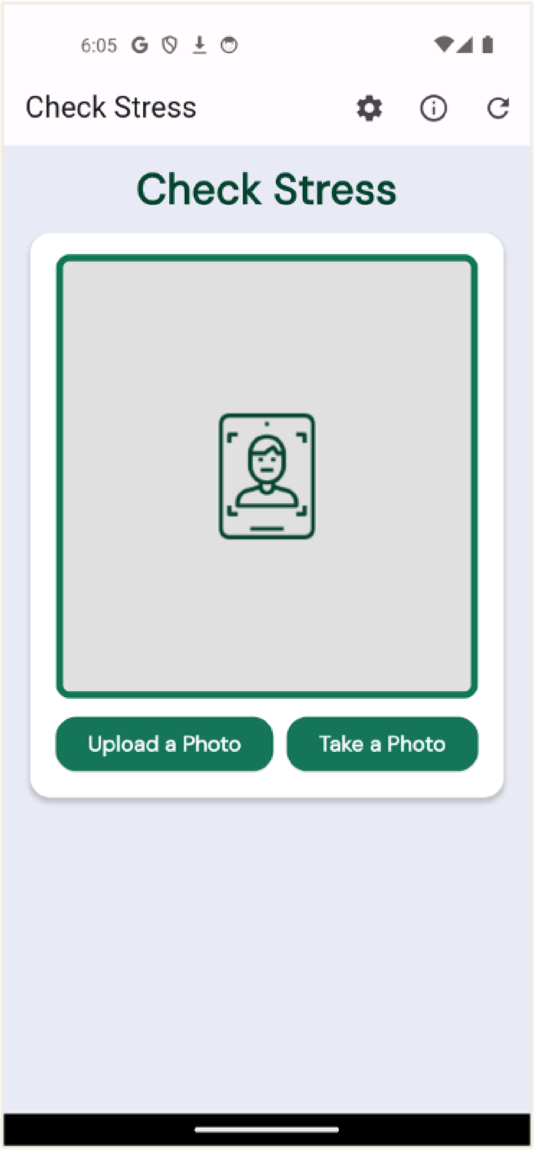

Figure 10. Stress Detector Interface

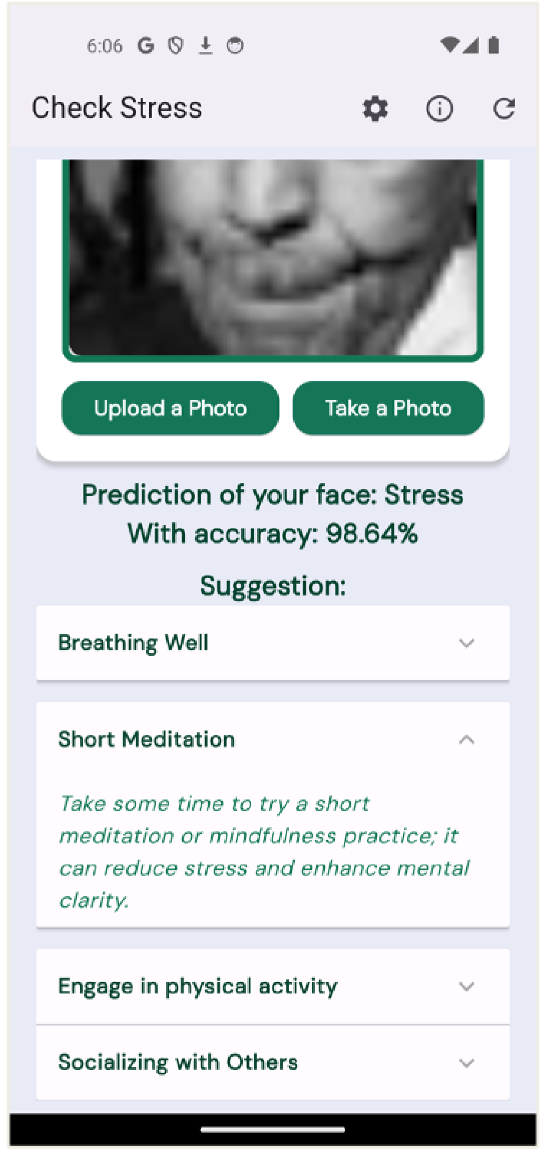

Figure 11. Advice Interface

the screen, allowing users to evaluate the reliability of the detection result. Furthermore, the application also provides practical advice to help manage or reduce stress. The user interface for the "Stress Detector" and "Advice" features are displayed in Figures 10 and 11.

The "Advice" feature is designed to assist users in managing or preventing stress. There are two types of advice: one for individuals detected as experiencing stress and another for those not. The application will display tips for reducing stress for users whose analysis results indicate stress. Meanwhile, for users detected as free from stress, the application will provide recommendations to maintain that state to avoid stress in the future. The list of advice provided can be seen in Tables II and III below.

TABLE II. List Of Advice For Stress Category

Advice	Reference
Breathe Properly	[41]
Short Meditation	[42]
Engaging in Physical Activity	[43]
Socializing with Others	[44]

TABLE III. List Of Advice For Non-Stress Category

Advice	Reference
Maintain Rest Time	[45]
Engage in Hobbies	[46]
Relaxation	[42]
Learn Stress Management	[47]

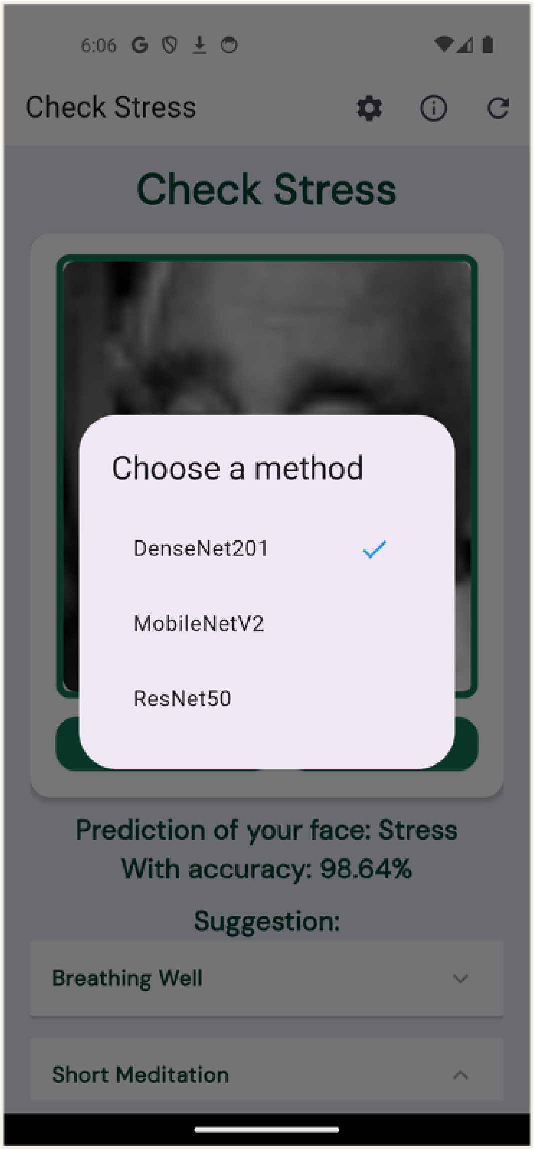

Figure 12. Architecture Settings Interface

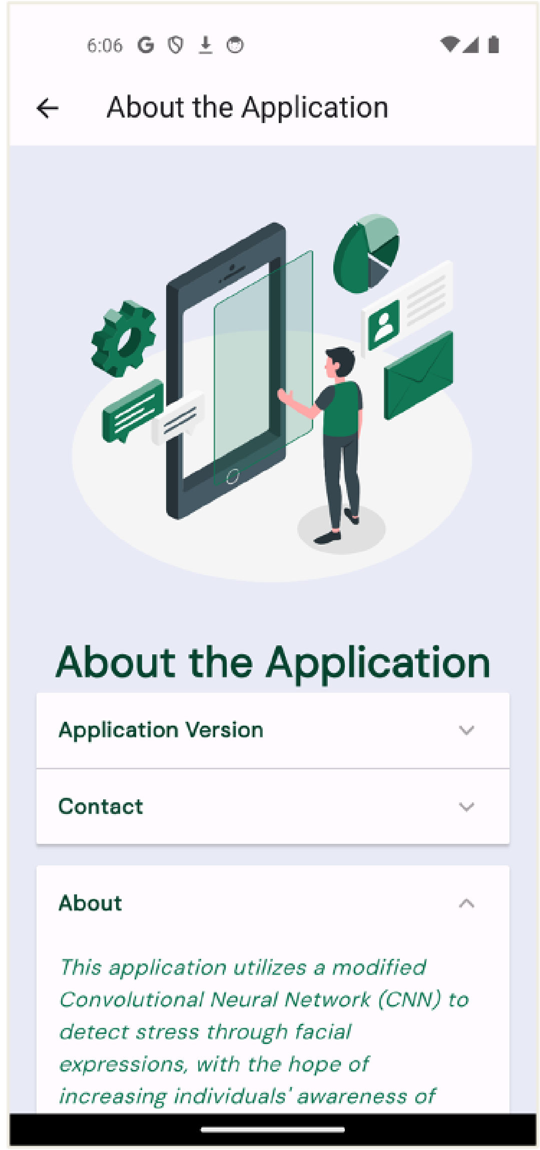

Figure 13. About Interface

The ”Settings” feature is designed to support exploration and research in stress detection by providing access to various previously trained architectures. This feature gives users control over selecting an architecture based on specific research needs and facilitates a deeper understanding of how different architectures can affect detection results. In the context of research and development, users can take advantage of this option to directly compare the effectiveness of various architectures, highlighting the architecture that shows the best performance under certain conditions as a reference. The display of the settings interface is presented in Figure 12.

The final feature of this application summarizes all available features, including the source of the advice provided, the stress facial image dataset used for training, the contact person that can be reached, and other relevant information. To view the display of the ”About” feature, you can see Figure 13 provided below.

This application has the potential to be highly beneficial for users in managing stress. By providing accurate stress detection and practical advice, users can better understand their stress levels and take proactive steps to manage or reduce stress effectively. This tool can be an essential part of personal stress management strategies, offering users a convenient way to monitor and address stress in their daily lives.

After all features in the application were completed, blackbox testing was performed to ensure the applica-

TABLE IV. Blackbox Testing

Test Case	Scenario	Expected Result	Actual Result	Status
Stress Detection	Upload/Capture Image	Correctly identify stress status and display accuracy	Successfully identified stress status	Passed
Advice	View Advice	Display appropriate advice based on stress status	Provided relevant advice for both stress and non-stress categories	Passed
Architecture Settings	Select Different Architectures	Allow selection and comparison of various architectures	Enabled seamless selection and comparison of different architectures	Passed
About Page Navigation	Navigate to About Page	Correctly display the About page with all relevant information	Successfully displayed the About page with all relevant information	Passed

tion's functionality and user experience met the desired requirements, focusing on verifying outputs against expected results. Validation scenarios were conducted across all features. Detailed results, including test cases and final outcomes, are documented in Table IV. All test cases passed successfully.

While the modifications improved accuracy from 75.90% to 77.83%, the gains were modest. Future work will focus on significantly increasing accuracy by exploring advanced data augmentation techniques, developing hybrid models that combine CNNs with other machine learning methods, utilizing transfer learning from larger datasets, creating ensemble models, optimizing hyperparameters, and incorporating multimodal data sources such as physiological signals. These strategies aim to achieve more substantial improvements in stress detection through facial analysis. Additionally, future work will include user testing to evaluate the application's usability and effectiveness in real-world scenarios. This will involve gathering feedback from users to refine the application further and ensure it meets their needs in managing and detecting stress effectively.

5. CONCLUTION

The primary objective of this research was the development of a mobile application that leverages artificial intelligence for personal stress detection. This research has demonstrated the significant potential of artificial intelligence, particularly Convolutional Neural Networks (CNN), in detecting stress through facial expression analysis. By modifying existing CNN architectures such as DenseNet201, MobileNetV2, and ResNet50, the study achieved notable improvements in detection accuracy, with the modified DenseNet201 attaining the highest accuracy of 77.83%. These findings underscore the effectiveness of AI technology in enhancing stress detection from facial expressions, addressing crucial gaps in the field.

The application showcases significant advancements in technology for mental health, featuring capabilities such as stress detection based on facial analysis, practical stress management advice, customizable settings for deep learning architecture, and comprehensive application information. This mobile application provides a practical, user-friendly solution, highlighting the potential impact of these findings on stress management.

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References

[1] A. Yulinda, D. Suriany, and S. Suciaty, "Analisis hubungan antara tingkat stres dengan status gizi siswa sd di kota palu," 2019.

[2] N. T. L. Gaol, "Teori stres: Stimulus, respons, dan transaksional," *Buletin Psikologi*, vol. 24, p. 1, 6 2016.

[3] M. E. Riyadi, A. Wiguna, R. V. Kusumasari, F. D. Kurniati, and S. S. Global, "Spiritualitas berhubungan dengan stres pada mahasiswa keperawatan yang mengerjakan skripsi," *Jurnal Manajemen Asuhan Keperawatan*, vol. 7, pp. 52–57, 2023.

[4] J. J, Y. Phoebe, S. Aurelia, and Pandina, "Kesadaran diri terhadap stress yang dirasakan," 7 2020.

[5] M. Pediaditis, G. Giannakakis, and F. Chiarugi, "Extraction of facial features as indicators of stress and anxiety," 2015.

[6] A. G. Yuli, M. H. Widhiastuti, and P. R. Dewi, *STRES KERJA*, 2018.

[7] D. Manousos, G. Iatraki, E. Christinaki, M. Pediaditis, F. Chiarugi, M. Tsiknakis, and K. Marias, "Contactless detection of facial signs related to stress: A preliminary study." Institute for Computer Sciences, Social Informatics and Telecommunications Engineering (ICST), 12 2014.

[8] Y. S. Can, B. Arnrich, and C. Ersoy, "Stress detection in daily life scenarios using smart phones and wearable sensors: A survey," 4 2019.

[9] W.-T. Chew, S.-C. Chong, T.-S. Ong, and L.-Y. Chong, "Facial expression recognition via enhanced stress convolution neural network for stress detection," 2022.

[10] A. Y. Saleh and L. K. Xian, "Stress classification using deep learning with 1d convolutional neural networks," *Knowledge Engineering and Data Science*, vol. 4, p. 145, 12 2021.

[11] J. Almeida and F. Rodrigues, "Facial expression recognition system for stress detection with deep learning," vol. 1. Science and Technology Publications, Lda, 2021, pp. 256–263.

[12] H. Zhang, L. Feng, N. Li, Z. Jin, and L. Cao, "Video-based stress detection through deep learning," *Sensors (Switzerland)*, vol. 20, pp. 1–17, 10 2020.

[13] A. Kene and S. Thakare, "Mental stress level prediction and classification based on machine learning," 2021, pp. 1–7.

[14] D. Konar, S. De, P. Mukherjee, and A. H. Roy, "A novel human stress level detection technique using eeg," 2023, pp. 1–6.

[15] P. Garg, J. Santhosh, A. Dengel, and S. Ishimaru, "Stress detection by machine learning and wearable sensors." Association for Computing Machinery, 2021, pp. 43–45.

[16] H. Angalakuditi and B. Bhowmik, "Stress detection using deep learning algorithms," 2023, pp. 1–7.

[17] R. Hanchate, H. Narute, and S. Shavage, "Stress detection using machine learning," *International Journal of Science and Healthcare Research*, vol. 8, pp. 307–311, 5 2023.

[18] S. Vaikole, S. Mulajkar, A. More, P. Jayaswal, and S. D. A. Professor, "Stress detection through speech analysis using machine learning," pp. 2320–28 820, 2020. [Online]. Available: www.ijcrt.org

[19] K. Jadhav and P. Vanwari, "Detecting stress based on social interactions in social networks," 2019. [Online]. Available: www.jetir.org98

[20] H. T. Mokui, dan S. N. Alam, and C. Author, "Sistem pendeteksi stres pada manusia menggunakan metode fuzzy logic berbasis internet of things," 2022. [Online]. Available: https://elektroda.uho.ac.id/

[21] G. Giannakakis, D. Grigoriadis, K. Giannakaki, O. Simantiraki, A. Roniotis, and M. Tsiknakis, "Ieee transactions on affective computing, manuscript id 1 review on psychological stress detection using biosignals," 2019.

[22] A. S. Stramari, M. F. Catapan, and C. S. Strobel, "Method for stress detection in industrial assemblers using smartwatch sensors," *Revista de Gestao Social e Ambiental*, vol. 17, 2023.

[23] R. Ahuja and A. Banga, "Mental stress detection in university students using machine learning algorithms," vol. 152. Elsevier B.V., 2019, pp. 349–353.

[24] T. Iqbal, A. Elahi, W. Wijns, and A. Shahzad, "Exploring unsupervised machine learning classification methods for physiological stress detection," *Frontiers in Medical Technology*, vol. 4, 2022.

[25] R. K. Nath, H. Thapliyal, and A. Caban-Holt, "Validating physiological stress detection model using cortisol as stress bio marker," 2020.

[26] L. Rachakonda, S. P. Mohanty, E. Kougianos, and P. Sundaravadivel, "Stress-lysis: A dnn-integrated edge device for stress level detection in the iomt," *IEEE Transactions on Consumer Electronics*, vol. 65, pp. 474–483, 2019.

[27] L. Rachakonda, A. Kothari, S. P. Mohanty, E. Kougianos, and M. Ganapathiraju, "Stress-log: An iot-based smart system to monitor stress-eating," 2019.

[28] N. E. Asha, Ehtesum-Ul-Islam, and R. Khan, "Low-cost heart rate sensor and mental stress detection using machine learning." Institute of Electrical and Electronics Engineers Inc., 6 2021, pp. 1369–1374.

[29] L. Zhu, P. C. Ng, Y. Yu, Y. Wang, P. Spachos, D. Hatzinakos, and K. N. Plataniotis, "Feasibility study of stress detection with machine learning through eda from wearable devices," vol. 2022-May. Institute of Electrical and Electronics Engineers Inc., 2022, pp. 4800–4805.

[30] Y. S. Can, N. Chalabianloo, D. Ekiz, and C. Ersoy, "Continuous stress detection using wearable sensors in real life: Algorithmic programming contest case study," *Sensors (Switzerland)*, vol. 19, 4 2019.

[31] S. Haque, Z. Eberhart, A. Bansal, and C. McMillan, "Semantic similarity metrics for evaluating source code summarization," vol. 2022-March. IEEE Computer Society, 2022, pp. 36–47.

[32] V. Sudha, S. Kaviya, S. Sarika, and R. Raja, "Stress detection based on human parameters using machine learning algorithms," 2022. [Online]. Available: https://ssrn.com/abstract=4031942

[33] T. L. Prasanthi and K. Prasanthi, "Machine learning-based signal processing by physiological signals detection of stress," pp. 4831–4840, 2021.

[34] J. Ukwattage, "Stress faces dataset," 12 2022. [Online]. Available: https://www.kaggle.com/datasets/janithukwattage/stress-faces-dataset

[35] W. Suartika, A. Y. Wijaya, and R. Soelaiman, "Klasifikasi citra menggunakan convolutional neural network (cnn) pada caltech 101," 2016.

[36] S. Abdulhamit, K. Tugce, O. Fatih, D. Sengul, and T. Turker, "Feature extraction and fusion using deep convolutional neural networks for covid-19 detection using ct and x-ray images," *World Journal of Advanced Research and Reviews*, vol. 19, pp. 914–933, 7 2023.

[37] N. Srivastava, G. Hinton, A. Krizhevsky, and R. Salakhutdinov, "Dropout: A simple way to prevent neural networks from overfitting," pp. 1929–1958, 2014.

[38] D. Scherer, A. Müller, and S. Behnke, "Evaluation of pooling

operations in convolutional architectures for object recognition," 2010. [Online]. Available: http://www.ais.uni-bonn.de

[39] V. Nair and G. E. Hinton, "Rectified linear units improve restricted boltzmann machines," 2010.

[40] E. Bisong, "Tensorflow 2.0 and keras," *Building Machine Learning and Deep Learning Models on Google Cloud Platform*, 2019. [Online]. Available: https://api.semanticscholar.org/CorpusID:204628587

[41] X. Ma, Z. Q. Yue, Z. Q. Gong, H. Zhang, N. Y. Duan, Y. T. Shi, G. X. Wei, and Y. F. Li, "The effect of diaphragmatic breathing on attention, negative affect and stress in healthy adults," *Frontiers in Psychology*, vol. 8, 6 2017.

[42] X. Zuo, Y. Tang, Y. Chen, and Z. Zhou, "The efficacy of mindfulness-based interventions on mental health among university students: a systematic review and meta-analysis," 2023.

[43] X. Wang, Z. dong Cai, W. ting Jiang, Y. yan Fang, W. xin Sun, and X. Wang, "Systematic review and meta-analysis of the effects of exercise on depression in adolescents," 12 2022.

[44] J. Holt-Lunstad, "Social connection as a public health issue: The evidence and a systemic framework for prioritizing the "social" in social determinants of health," *Annu. Rev. Public Health*, vol. 43, pp. 193–213, 2022. [Online]. Available: https://doi.org/10.1146/annurev-publhealth-

[45] A. J. Scott, T. L. Webb, M. M.-S. James, G. Rowse, and S. Weich, "Improving sleep quality leads to better mental health: A meta-analysis of randomised controlled trials," 12 2021.

[46] Z. Li, J. Dai, N. Wu, Y. Jia, J. Gao, and H. Fu, "Effect of long working hours on depression and mental well-being among employees in shanghai: The role of having leisure hobbies," *International Journal of Environmental Research and Public Health*, vol. 16, 12 2019.

[47] E. B. Algorani and V. Gupta, "Coping mechanisms," 2023.