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# Deep Learning-Based Stress Identification in Children: Unraveling Physiological Patterns

**Hima Vijayan V P*[1], Asif Shahkutty[2], Akshay S[3]**

Department of Electronics & Communication Engineering, ACE College Of Engineering, APJ Abdul Kalam Technological University, Kerala, India[1-3]

**Abstract:** Stress detection in children is a critical concern, given its profound impact on their well-being. This paper proposes a novel approach for identifying stress levels in children by analyzing physiological parameters, namely human body humidity, temperature, and step count. Leveraging deep learning techniques, we aim to develop a model capable of discerning stress levels, ultimately aiding in early intervention and support.

**Index Terms:** Deep Learning, Stress Identification, Child Health, Physiological Parameters, Body Humidity, Body Tem- perature, Step Count.

## I. INTRODUCTION

Childhood stress has become a prevalent issue affecting the lives of many young individuals. The identification and mitigation of stress in children are of paramount importance as prolonged exposure to stressors can lead to adverse con- sequences, both immediate and long-term [1].

To address this concern, our research focuses on utilizing advanced technol- ogy, specifically deep learning, to develop a stress detection system based on three key physiological parameters: body humidity, body temperature, and step count.

### *A. Statistical Significance of the Problem*

Statistically, stress in children is on the rise, with various environmental, societal, and academic factors contributing to its prevalence[2].

According to recent studies, a significant percentage of children experience stress-related symptoms, impacting their physical health, academic performance, and emotional well-being. Recognizing stress in its early stages is crucial for implementing timely interventions and support mechanisms.

One of the challenges in identifying stress in children is the dynamic nature of stressors and the varied manifestations of stress across different individuals.

Traditional methods of stress assessment often rely on subjective measures such as self-reporting or observer assessments, which may not capture subtle changes in physiological parameters[3]. This calls for innovative approaches that leverage technology and data- driven methodologies.

### *B. Rationale for Using Physiological Indicators*

Understanding the physiological aspects of stress in chil- dren provides a holistic perspective. Body humidity, body temperature, and step count are reliable indicators of an individual’s overall well-being[4].

Changes in these parameters have been linked to stress responses, making them valuable for developing an objective and non-invasive stress detection system

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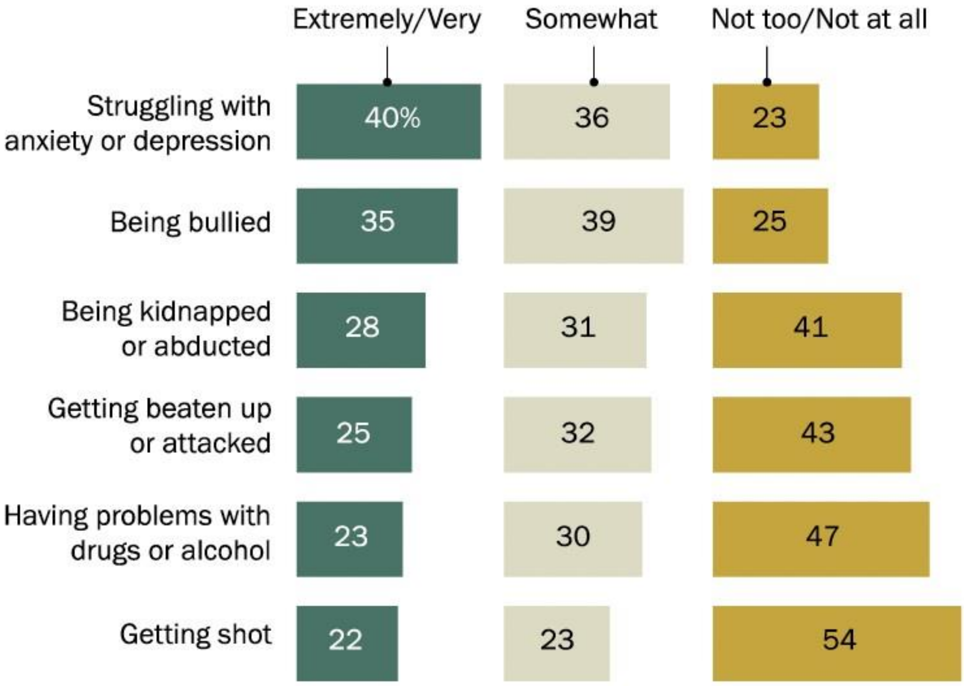


Fig. 1. Stress in children and parental concern [4]

## II. ROLE OF DEEP LEARNING

Deep learning plays a pivotal role in the proposed approach for the identification of stress [5] in children using physiological indicators such as body humidity, body temperature, and step count. Here are several key aspects of the role of deep learning in this context:

### *A. Complex Pattern Recognition*

Deep learning models are well-suited for recognizing in- tricate patterns and relationships within large and complex datasets. In the case of stress detection, physiological indi- cators are likely to exhibit nuanced patterns that may be challenging to capture using traditional methods. Deep learning excels in automatically learning hierarchical features from the input data.

### *B. Feature Representation*

The multiple layers in a deep learning model enable the automatic extraction and representation of features from the input data. In the proposed model, these features correspond to variations in body humidity, body temperature, and step count that are indicative of stress levels. The hierarchical feature representation helps the model discern subtle changes in physiological parameters associated with stress.

### *C. Non-linearity and Adaptability*

Deep learning models, particularly neural networks with non-linear activation functions, can model complex, non-linear relationships in the data. Stress responses are multifaceted and can vary across individuals [6]. The flexibility of deep learning models allows them to adapt to the diverse and dynamic nature of stress indicators.

### *D. End-to-End Learning*

Deep learning models facilitate end-to-end learning, where the model learns directly from the raw input data to produce the desired output (in this case, stress level classification). This eliminates the need for manual feature engineering, allowing the model to automatically discover relevant patterns and relationships in the data.

### *E. Transfer Learning and Generalization*

Transfer learning techniques can be employed to leverage knowledge gained from pre-trained models on large datasets. This is particularly beneficial when working with a limited dataset, as the model can generalize well to new and unseen instances. The ability to generalize is crucial for deploying stress detection models across diverse populations of children.

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*F. Real-time Monitoring*

Deep learning models can be optimized for efficient infer- ence, enabling real-time processing of data. This is especially important in the context of stress detection in children, where timely interventions can have a significant impact. Real-time monitoring can be facilitated through the integration of deep learning models into wearable devices or health applications.

*G. Adaptation to Individual Variances*

Deep learning models can adapt to individual variances in stress responses [7]. Children may exhibit different physiological reactions to stress based on factors such as age, health status, and environmental conditions. The inherent adaptability of deep learning models allows them to account for these individual variations.

## III. METHODOLOGY

*A. Dataset*

The dataset used is Stress-Lysis.csv [8].Here, the stress levels of human beings are identified and examined based on their physical activity. A dataset including 2001 samples is offered for body temperature, humidity, and step count of the user. There are three distinct stress categories used: low, normal, and high stress. Dataset Columns:

- Humidity: Human body humidity levels.
- Temperature: Human body temperature.
- Step count: The number of steps taken by the individual.
- Stress levels: Classified into three categories - low stress, normal stress, and high stress.

*B. Work flow*

The initial step revolves around gathering comprehensive data from children, focusing on essential physiological parameters such as body humidity, body temperature, and step count. This dataset forms the foundation for our investigation into stress levels, as these indicators are considered integral reflections of an individual's physical activity. Our objective is to harness the power of deep learning to delve into the intricate relationships between these physiological features and the corresponding stress levels experienced by children.

To achieve this, we employ a sophisticated deep-learning model that is capable of unraveling complex patterns inherent in the collected dataset. The architecture of the model [9] is structured with layers dedicated to input, hidden, and output functionalities. Each layer is equipped with appro- priate activation functions designed to capture the nuanced relationships present in the data. The deep learning model is then trained using a diverse dataset, ensuring the inclusion of variations in stress responses across different age groups and individual characteristics. This diversity enhances the model's adaptability to the complexities of stress manifestation in a heterogeneous population. The training process involves optimizing the model through the utilization of an optimizer, a crucial component for ad- justing parameters to minimize errors. Following the training phase, the model's performance undergoes meticulous evalua- tion through rigorous testing on an independent dataset. This testing phase aims to assess the model's ability to generalize and accurately predict stress levels beyond the confines of the training data. The rigorous evaluation process ensures the reliability and robustness of our deep learning approach in identifying and understanding stress in children through physiological indicators.

The optimizer used in the context of deep learning plays a pivotal role in enhancing the model's performance during the training phase[10]. The optimizer is responsible for adjusting the parameters of the neural network to minimize the error or loss function [11]. In the provided methodology, the choice of the optimizer is specified as 'Adam.'

Adam (short for Adaptive Moment Estimation) is a pop- ular optimization algorithm in deep learning. It combines the benefits of two other optimization techniques: RMSprop (Root Mean Square Propagation) and Momentum. The key advantages of using the Adam optimizer include:

*1) Adaptability to Varying Learning Rates:* Adam dynami- cally adjusts the learning rates for each parameter in the neural network. This adaptability is particularly beneficial when deal- ing with different features and their gradients, enabling faster convergence [12].

*2) Efficient Memory Utilization:* The algorithm maintains an exponentially decaying average of past gradients and squared gradients[13], which helps in efficient memory utiliza- tion. This is especially relevant for large datasets and complex models.

*3) Momentum for Accelerated Convergence:* Adam incor- porates the concept of momentum, which helps accelerate

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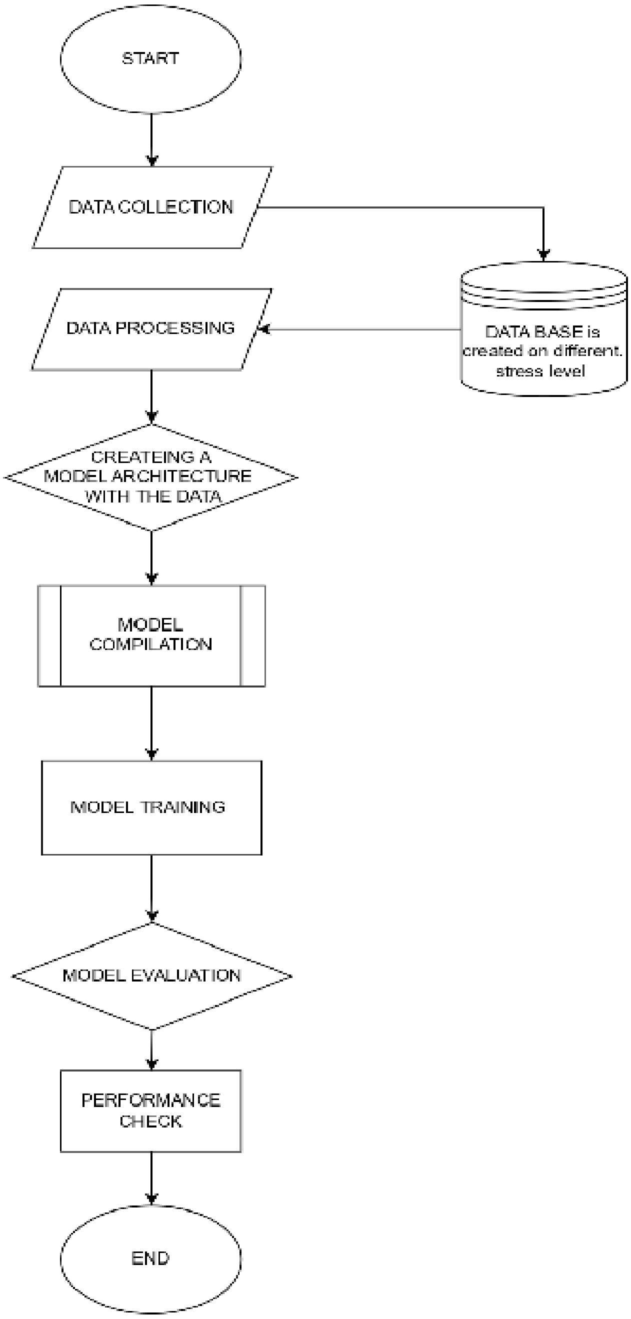


Fig. 2. Methodology Employed

convergence, especially in the presence of noisy gradients [14]. Momentum allows the optimizer to continue moving in the right direction, even when encountering irregularities in the gradient landscape. Effective Handling of Sparse Gradients:

Adam is effective in handling sparse gradients, making it suitable for scenarios where not all parameters have gradients at each iteration. While Adam is a popular choice, the effectiveness of an optimizer can vary based on the specific characteristics of the dataset and the nature of the problem being addressed. In some cases, researchers might experiment with different optimizers to find the one that performs best for their particular use case [15].

Overall, the selection of the Adam optimizer in the provided methodology suggests consideration for a well-established and versatile optimization algorithm, contributing to the efficiency and effectiveness of the deep learning model's training process.

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## IV. RESULTS

The dataset is split into training and testing sets. The model is trained on the training set and evaluated on the testing set. Training involves adjusting the model's parameters to minimize the loss function. Evaluation provides insights into the model's performance, measured using metrics such as accuracy. Visualization tool confusion matrices aid in

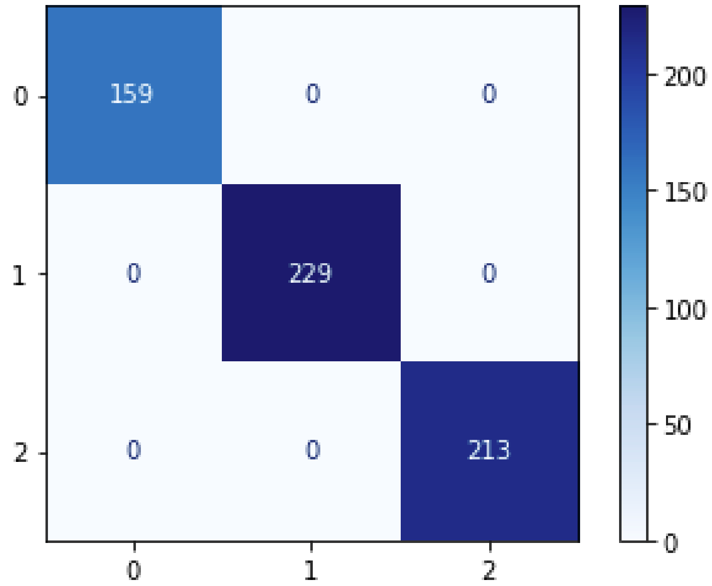


Fig. 3. Confusion Matrix

Accuracy: 1.0
Kappa Score: 1.0

Fig. 4. Accuracy

understanding how well the model is distinguishing between different stress levels. The accuracy 0f 100% is obtained as shown in Fig.4

Cohen's Kappa coefficient, often referred to as the Kappa score or simply Kappa, is a statistical measure that assesses the level of agreement between two raters beyond what would be expected by chance. It is commonly used in classification problems where two raters (or methods) assign categorical labels to a set of items.

Cohen's Kappa is particularly useful when dealing with imbalanced datasets or situations where chance agreement might be significant.

It ranges from -1 to 1, with the following interpretations:

1) Kappa = 1: Perfect agreement between raters.
2) Kappa = 0: Agreement equivalent to chance.
3) Kappa ¡ 0: Less agreement than expected by chance.

## V. CONCLUSION

Human stress detection is a critical aspect of promoting mental and physical well-being. Using deep learning tech- niques on the "Stress-Lysis.csv" dataset, we've demonstrated a methodology for building a stress detection model. The model's success lies in its ability to learn complex relation- ships between body humidity, body temperature, step count, and stress levels.

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## VI. FUTURE SCOPE

As technology continues to advance, integrating such mod- els into wearable devices or health applications can provide real-time stress monitoring and personalized interventions, contributing to a healthier and more resilient society

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