

Volume 11, Issue 11, November 2022



Impact Factor: 8.118











||Volume 11, Issue 11, November 2022||

| DOI:10.15680/IJIRSET.2022.1111113 |

A Vocal Expression Based on Student Stress Monitoring in IOT Environment

Dr. V.KAVITHA, P.ABHITHYA

Professor, Department of Computer Science and Engineering, Velalar College of Engineering and Technology,

Thindal, Erode, India

PG Student, Department of Computer Science and Engineering, Velalar College of Engineering and Technology,

Thindal, Erode, India

ABSTRACT: In this era of digital and modern education, the existence of psychological stress on students cannot be denied. The surplus aggregation of the stress may lead to different problems like a decline in student grade (performance), an increase of violence in behavior, and even more extreme cases. The previous studies are used the Bidirectional Long Short Term Memory for identify the students stress. But, it's not produce the efficient result in the simulation environment. Therefore need a new method to achieve the result. In the proposed system we modify the network which is replace the RNN with the CNN. Its produce the enhanced result. The proposed system going to identify the user Stress based on their vocal. They can directly interact the developed system its record voice and analysis it. After analysis its shows student stress details.

I. INTRODUCTION

Speech is one of the most complex, but it is also one of the most important human motor skills. We use speech to inform others about our environment and to exchange information about our current physical and mental state in both private and professional contexts. IoT systems are open It has been developed with architecture and is an integral part of the educational ecosystem. The system consists of two elements: one that measures vital signs to detect student stress, and one that controls stress. The system should be effective in minimizing agitation and reducing future stress. Speech production and processing relies on the interaction of approximately 100 muscles innervated by a diverse network of cranial and spinal nerves, subcortical and cortical parts of the brain, and cardiopulmonary processes. Speech is therefore a psychophysiological process influenced by environmental and internal challenges. Where human performance requires advance capabilities, but environmental and task-related situations make it difficult to effectively monitor stress. Stress can be caused by situations and activities that take a toll on a person's mind and body. Everyone responds differently to stress, as does their ability to cope with difficult or demanding situations. This device tracks stress and allows people to be alerted to their stress levels. This helps reduce stress to levels that cause serious health problems. Since physical and mental well-being are closely related, tracking and evaluating physiological and physical changes can be used to identify stress levels in humans. Predict a student's stress level.

II. LITERATURE REVIEW

1. A comprehensive framework for student stress monitoring in fog-cloud IoT environment: m-health perspective

Over the last few years, Internet of Things (IoT) has opened the doors to innovations that facilitate interactions among things and humans [1]. Focusing on healthcare domain, IoT devices such as medical sensors, visual sensors, cameras, and wireless sensor network are leading this evolutionary trend. In this direction, the paper proposes a novel, IoT-aware student-centric stress monitoring framework to predict student stress index at a particular context. Bayesian Belief Network (BBN) is used to classify the stress event as normal or abnormal using physiological readings collected from medical sensors at fog layer [1]. Abnormal temporal structural data which is time-enriched dataset sequence is analyzed for various stress-related parameters at cloud layer. To compute the student stress index, a two-stage Temporal Dynamic Bayesian Network (TDBN) model is formed.



||Volume 11, Issue 11, November 2022||

| DOI:10.15680/IJIRSET.2022.1111113 |

2. A Real-Time Human Stress Monitoring System Using Dynamic Bayesian Network

We present a real time non-invasive system that infers user stress level from evidences of different modalities. The evidences include physical appearance extracted from video via visual sensors, physiological conditions collected from an emotional mouse, behavioural data from user interaction activities with the computer, and performance measures [2]. We provide a Dynamic Bayesian Network (DBN) framework to model the user stress and these evidences. We describe the computer vision techniques we used to extract the visual evidences, the DBN model for modelling stress and the associated factors, and the active sensing strategy to collect the most informative evidences for efficient stress inference [2].

3. Genetic Algorithm-Based Human Mental Stress Detection and Alerting in Internet of Things

Healthcare is one of the emerging application fields in the Internet of Things (IoT). Stress is a heightened psychophysiological condition of the human that occurs in response to major objects or events. Stress factors are environmental elements that lead to stress [3]. A person's emotional well-being can be negatively impacted by long-term exposure to several stresses affecting at the same time, which can cause chronic health issues. To avoid strain problems, it is vital to recognize them in their early stages, which can only be done through regular stress monitoring. Wearable gadgets offer constant and real information collecting, which aids in experiencing an increase [3]. An investigation of stress discovery using detecting devices and deep learning-based is implemented in this work.

4. Detection of stress using wearable sensors in IoT platform

The proposed work concentrates on developing an IoT system which can efficiently detect the stress level of a person and provide a feedback which can assist the person to cope with the stressors. The system consists of a smart band module and a chest strap module which can be worn around wrist and chest respectively [4]. Stress is a natural reaction to various stress-inducing factors which can lead to physiologicaland behavioral changes. If persists for a longer period, stress can cause harmful effects onour body. The body sensors along with the concept of the Internet of Things can provide richinformation about one's mental and physical health [4]. The proposed work concentrates ondeveloping an IoT system which can efficiently detect the stress level of a person andprovide a feedback which can assist the person to cope with the stressors.

5. Towards IoT-enabled multimodal mental stress monitoring

Stress is a body's natural way of responding to any kind of demand or challenge that everyone experiences from time to time. Although short-term stress typically does not impose a health burden, exposure to prolonged stress can lead to significant adverse physiological and behavioral changes [5]. Coping with the impact of stress is a challenging task and in this context, stress assessment is essential in preventing detrimental long-term effects [5]. The public embracement of connected wearable Internet of Things (IoT) devices, as well as the proliferation of Artificial Intelligence (AI) and Machine Learning (ML) technologies, have generated new opportunities for personalized stress tracking and management.

6. Factors affecting education technology success

The purpose of this paper is to examine particular and relevant factors that affect the outcome or implementation of educational technology approaches in school classrooms [6]. The analysis inspects factors that affect education success in general, but we concentrate on how they specifically affect technology as an enhancement to integrated teaching [6]. The presumption is that technology magically makes everything (tasks, learning, humaninteraction, etc.) "better".

III. SYSTEM STUDY

EXISTING SYSTEMS

Educational teaching and learning methods have evolved over time. Digitization and modern education, psychological stress on students cannot be denied. Accumulated stress can lead to a variety of problems, including: Declining student performance (achievement), increasing violence, and even extreme cases. Existing systems use extended VGG16, Bidirectional Long-Short-Term Memory Network (Bi-LSTM), and multinomial naive Bayesian methods to generate sentiment ratings from student facial expressions, speech pitch, and student language content. increase. Events that stress students. Specifically, the model classifies stressful events as normal or abnormal based on the overall emotion of the student's physiological data readings. Students at high risk of depression should be constantly monitored to avoid

International Journal of Innovative Research in Science, Engineering and Technology (IJIRSET)



| e-ISSN: 2319-8753, p-ISSN: 2347-6710| <u>www.ijirset.com</u> | Impact Factor: 8.118|

||Volume 11, Issue 11, November 2022||

| DOI:10.15680/IJIRSET.2022.1111113 |

health complications.

DISADVANTAGES

- ✓ It's providing the lowest accuracy.
- ✓ The cloud layer data are stored and processed .
- ✓ It's consumed the bandwidth and Data storage.
- ✓ Its consumes the result delay.

PROPOSED SYSTEM

Long short-term memory (LSTM) is commonly used as the basic unit of repetition in convolutional neural networks (CNN). However, traditional LSTMs assume that the state of the current time step depends on the previous time step. This assumption limits the power of time-dependent modeling. In this work, we propose a new variant of LSTM, Advanced LSTM (A-LSTM), to achieve better temporal context modeling. Using A-LSTM in Weighted Pooling CNN for Emotion Recognition. We investigate the modeling ability of A-LSTM in the form of speech-based emotion recognition. Improve the voice user experience by recognizing emotions based on real-world voices.

IV. METHODOLOGY

IOT LAYER

- This layer raw data is collected from IOT-enabled input devices on microphones and it installed around the student observation.
- It would act as primary source of fetching data from real-world entites.
- The data is fetched at the IOT layer is then passed to then fog layer over the internet and is possible with the integration of internet enabled smart devices.
- In this IOT layer it is utilized to analyzed sudents under severe stress conditions at the earliest stages to decrease the dropout rates in the education system.
- The IOT devices is at the data acquisition layer and then fog layer act as a between IOT layer.

FOG LAYER

- Data acquired from acquisition layer is further transmitted to fog layer for classifying the stress data into different classes.
- The heterogeneous attributes generated from IoT sensors include direct and indirect health-oriented attributes.
- If fog layer does not loading unnecessary data from another layer which force result is more high and increase the complexity.
- The fog layer performed all data transmission task. Hence the data is processed at the fog layer to save network and increase the overall performance.

STRESS PREDICTION

- This module is composed of CNN layers and fully connected layers.
- The neural network layers capture the temporal information of the extracted features and calculate the frame-level output at every time sequence f = f1, f2, ..., fT
- The frame-level output is converted to a level feature that embraces the entire characteristics before feeding it into the fully-connected layer.
- The predictions are made by using trained weights and are generated for the cases where the stress readings are enabling the stress event.
- These parameters are used to adopt the most suitable techniques to facilitate the development of stress measuring process.

ADVANCED LSTM

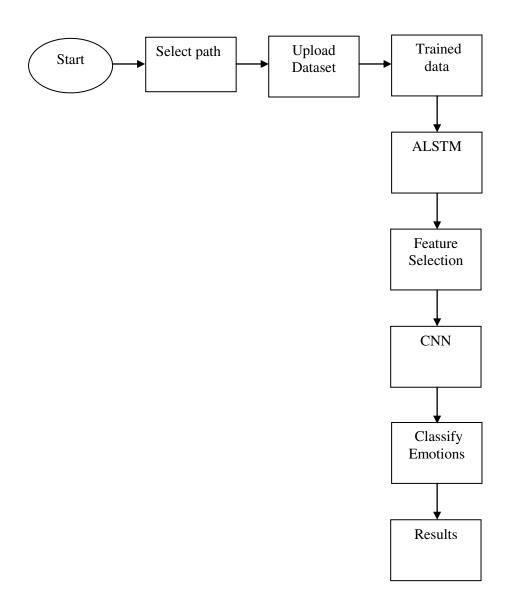
- To validate A-LSTM in the application of categorical emotion classification Conventional LSTM tasks take the output from lower layer and previous step as input and feed value to higher layer.
- The gating mechanism is used to control information flow by point-wise multiplication.



||Volume 11, Issue 11, November 2022||

| DOI:10.15680/IJIRSET.2022.1111113 |

ARCHITECTURE DIAGRAM



V. CONCLUSION

This paper proposed a new type of LSTM, A-LSTM. It is and early work with A-LSTM. We used it in a weighted pooling RNN for emotion recognition. It is shown that A-LSTM can outperform traditional LSTM under weighted pooling RNN framework with few additional parameters. This improvement takes advantage of the flexible time-dependent modeling capabilities of A-LSTM. The goal is to predict stressful emotions early on to avoid undesirable situations such as poor grades and increased absenteeism from school and college. When enforcement is important in the education system and anticipates stress.

REFERENCES

1. Prabal Verma & Sandeep K Sood, "A comprehensive framework for student stress monitoring in fog-cloud IoT environment: m-health perspective". *Medical & Biological Engineering & Computing* volume 57, pages231–244



||Volume 11, Issue 11, November 2022||

| DOI:10.15680/IJIRSET.2022.1111113 |

(2019).

- 2. Wenhui Liao, Zhiwei Zhu, Qiang Ji, "A Real-Time Human Stress Monitoring System Using Dynamic Bayesian Network". July 2015, Proceedings / CVPR. IEEE Computer Society Conference on Computer Vision and Pattern Recognition, DOI:10.1109/CVPR.2005.394.
- 3. Hatem S. A. Hamatta, ¹Kakoli Banerjee, Harishchander Anandaram, Mohammad Shabbir Alam, ⁴C. Anand Deva Durai, B. Parvathi Devi, Hemant Palivela, R. Rajagopal, and Alazar Yeshitla, "Genetic Algorithm-Based Human Mental Stress Detection and Alerting in Internet of Things", Aug 2022.
- 4. S. Uday, C. Jyotsna, and J. Amudha, "Detection of stress using wearable sensors in IoT platform," in Proc. 2nd Int. Conf. Inventive Commun. Comput. Technol. (ICICCT), Apr. 2018, pp. 492–498.
- 5. M. Mozafari, F. Firouzi, and B. Farahani, "Towards IoT-enabled multimodal mental stress monitoring," in Proc. Int. Conf. Omni-layer Intell. Syst. (COINS), Aug. 2020, pp. 1–8.
- 6. J. Accuosti, "Factors affecting education technology success," in Proc. ASEE Zone I Conf., Apr. 2016, pp. 1–6. [8] B. Bruggeman, J. Tondeur, K. Struyven.
- 7. M. Bond, "Facilitating student engagement through the flipped learning approach in K-12: A systematic review," Comput. Educ., vol. 151, Jul. 2020, Art. no. 103819.
- 8. A.-J. Moreno-Guerrero, R. Soler-Costa, J.-A. Marín-Marín, and J. López-Belmonte, "Flipped learning and good teaching practices in secondary education," Comunicar, vol. 29, no. 68, pp. 107–117, Jul. 2021.
- 9. K. Ratih, M. F. J. Syah, N. Nurhidayat, S. Jarin, and J. Buckworth, "Learning patterns during the disruptive situation in informal education: Parents' efforts and challenges in the adjustment of progressive learning," Indonesian J. Learn. Adv. Educ., vol. 3, no. 3, pp. 180–193, 2021.
- 10. S. Hidi, "An interest researcher's perspective: The effects of extrinsic and intrinsic factors on motivation," in Intrinsic and Extrinsic Motivation, 2017, pp. 309–339.
- 11. M. Pulido-Martos, J. M. Augusto-Landa, and E. Lopez-Zafra, "Sources of stress in nursing students: A systematic review of quantitative studies," Int. Nursing Rev., vol. 59, no. 1, pp. 15–25, Mar. 2019.
- 12. J. B. Jemmott and S. E. Locke, "Psychosocial factors, immunologic mediation, and human susceptibility to infectious diseases: How much do we know?" Psychol. Bull., vol. 95, no. 1, pp. 78–108, 2015.
- 13. N. K. Giang, M. Blackstock, R. Lea, and V. C. M. Leung, "Developing IoT applications in the fog: A distributed dataflow approach," in Proc. 5th Int. Conf. Internet Things (IoT), Oct. 2015, pp. 155–162.
- 14. S. Masood, A. Rai, A. Aggarwal, M. N. Doja, and M. Ahmad, "Detecting distraction of drivers using convolutional neural network," Pattern Recognit. Lett., vol. 139, pp. 79–85, Nov. 2020.













INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH

IN SCIENCE | ENGINEERING | TECHNOLOGY







📵 9940 572 462 🔯 6381 907 438 🔀 ijirset@gmail.com

