ISSN 2277-2685
IJESR/June-2024/ Vol-14/Issue-2s/234—250
Mohd Ghouse Mohiuddin *et. al.,* / International Journal of Engineering & Science Research

PAIN RECOGNITION WITH PHYSIOLOGICAL SIGNALS USING MULTI-LEVEL CONTEXT INFORMATION

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ABSTRACT

In the medical field, automatic pain detection is crucial. Previous research has shown that physiological signal characteristics are used preferentially for traditional models by automated pain identification algorithms. These techniques work well, however they mostly depend on medical knowledge to extract physiological signal features. Regardless of medical background, this work proposes a deep learning strategy based on physiological signals that play the roles of both feature extraction and classification. We suggest including multidimensional contextual information for every physiological signal that distinguishes between pain and absence of discomfort. Based on Part A of the BioVid Heat Pain database and the Emopain 2021 dataset, our experimental findings demonstrate that multi-level context information performs more substantially than uni-level context information. Our experimental findings for pain detection tasks include Pain 0 and Pain 1, Pain 0 and Pain 2, Pain 0 and Pain 3, and Pain 0 and Pain 4 for Part A of the BioVid Heat Pain database. In a Leave-One-Subject-Out cross-validation analysis, the classification task between Pain 0 and Pain 4 yields average accuracy of 84.8 B1 13.3% for 87 patients and 87.8 B1 11.4% for 67 individuals. The suggested approach makes use of deep learning's superior performance over traditional techniques while handling physiological inputs. The author of the proposal used multilevel or two level feature selection algorithms, such as CNN + BI-LSTM. In the extension work, we added three levels of feature optimization by combining CNN + BI-LSTM + BI-GRU. In this way, BI-STM will select the CNN optimized features, and BI-GRU will select the BI-LSTM optimized features. Three level feature optimization and selection contributes to increased accuracy.

INTRODUCTION

The body's typical reaction to an ailment that needs medical care is pain. Conventional techniques for identifying pain mostly use subjective identification and human observations. During the course of treatment, physiotherapists use exercises to gauge a patient's level of discomfort and provide appropriate exercise regimens to help the patient manage their condition. The ability to recognize pain is based on observation, professional knowledge, and the patient's unique viewpoint as expressed via their expressions. The lack of consistent, dependable guidelines for identifying pain imposes several restrictions. As a result, people need to have pain recognition automated. Applications for pain recognition in medicine are a kind of health monitoring system that aids in patients' physical therapy recovery from disease. Behavior and physiology are used by pain recognition systems to carry out categorization tasks. Physiological signals, facial expressions, bodily movements, vocalizations, and other behaviors, alone or in combination, are examples of measures.

Recognizing pain from a patient's behavior is not always accurate. The patient has deliberate control over how they communicate their emotions. Additionally, the way that people convey their pain varies based on their personalities. Some patients go unconscious and are unable to dependably and effectively communicate their distressing feelings. It is challenging to identify pain from affective behavior. Consequently, it is crucial to recognize pain utilizing physiological cues.

PROBLEM STATEMENT

Current pain recognition methods rely heavily on subjective human observations, leading to limitations in accuracy and reliability. Patients may intentionally control emotional expressions, and individual personalities can influence pain behavior, making it challenging to obtain consistent and objective assessments. To address these issues, there is a pressing need for an automated pain recognition system that leverages physiological signals to ensure more accurate and universal pain assessment in the medical field.

LITERATURE SURVEY

Automatic Recognition Methods Supporting Pain Assessment: A Survey:

https://www.researchgate.net/publication/336447252_Automatic_Recognition_Methods_Supporting_Pain_Assessment_A_Survey

ABSTRACT: Pain is a complex phenomenon, involving sensory and emotional experience, that is often poorly understood, especially in infants, anesthetized patients, and others who cannot speak. Technology supporting pain assessment has the potential to help reduce suffering; however, advances are needed before it can be adopted clinically. This survey paper assesses the state of the art and provides guidance for researchers to help make such advances. First, we overview pain's biological mechanisms, physiological and behavioral responses, emotional components, as well as assessment methods commonly used in the clinic. Next, we discuss the challenges hampering the development and validation of pain recognition technology, and we survey existing datasets together with evaluation methods. We then present an overview of all automated pain recognition publications indexed in the Web of Science as well as from the proceedings of the major conferences on biomedical informatics and artificial intelligence, to provide understanding of the current advances that have been made. We highlight progress in both non-contact and contact-based approaches, tools using face, voice, physiology, and multi-modal information, the importance of context, and discuss challenges that exist, including identification of ground truth. Finally, we identify underexplored areas such as chronic pain and connections to treatments, and describe promising opportunities for continued advances.

The biovid heat pain database data for the advancement and systematic validation of an automated pain recognition system:

https://www.semanticscholar.org/paper/The-biovid-heat-pain-database-data-for-the-and-of-Walter-Gruss/c531a0105a597c9c3d1491daad8977d04b6f238e

ABSTRACT: The objective measurement of subjective, multi-dimensionally experienced pain is still a problem that has yet to be adequately solved. Though verbal methods (i.e., pain scales, questionnaires) and visual analogue scales are commonly used for measuring clinical pain, they tend to lack in reliability or validity when applied to mentally impaired individuals. Expression of pain and/or its biopotential parameters could represent a solution. While such coding systems already exist, they are either very costly and time-consuming, or have been insufficiently evaluated with regards to the theory of mental tests. Building on the experiences made to date, we collected a database using visual and biopotential signals to advance an automated pain recognition system, to determine its theoretical testing quality, and to optimize its performance. For this purpose, participants were subjected to painful heat stimuli under controlled conditions.

Deep Learning:

https://www.researchgate.net/publication/277411157_Deep_Learning

ABSTRACT: Deep learning allows computational models that are composed of multiple processing layers to learn representations of data with multiple levels of abstraction. These methods have dramatically improved the state-of-the-art in speech recognition, visual object recognition, object detection and many other domains such as drug discovery and genomics. Deep learning discovers intricate structure in large data sets by using the backpropagation algorithm to indicate how a machine should change its internal parameters that are used to compute the representation in each layer from the representation in the previous layer. Deep convolutional nets have brought about breakthroughs in processing images, video, speech and audio, whereas recurrent nets have shone light on sequential data such as text and speech.

The AffectMove 2021 Challenge - Affect Recognition from Naturalistic Movement Data:

https://ieeexplore.ieee.org/document/9666322

ABSTRACT: We ran the first Affective Movement Recognition (AffectMove) challenge that brings together datasets of affective bodily behaviour across different real-life applications to foster work in this area. Research on automatic detection of naturalistic affective body expressions is still lagging behind detection based on other modalities whereas movement behaviour modelling is a very interesting and very relevant research problem for the affective computing community. The AffectMove challenge aimed to take advantage of existing body movement datasets to address key research problems of automatic recognition of naturalistic and complex affective behaviour from this type of data. Participating teams competed to solve at least one of three tasks based on datasets of different sensors types and real-life problems: multimodal EmoPain dataset for chronic pain physical rehabilitation context, weDraw-l Movement dataset for maths problem solving settings, and multimodal Unige-Maastricht Dance dataset. To foster work across datasets, we also challenged participants to take advantage of the data across datasets to improve performances and also test the generalization of their approach across different applications.

Analysis of Facial Expressiveness During Experimentally Induced Heat Pain:

https://www.researchgate.net/publication/319316942_Analysis_of_Facial_Expressiveness_During_Experimentally_Induced_Heat_Pain

ABSTRACT: To develop automatic pain monitoring systems, we need a deep understanding of pain expression and its influencing factors and we need datasets with high-quality labels. This work analyzes the variation of facial activity with pain stimulus intensity and among subjects. We propose two distinct methods to assess facial expressiveness and apply them on the BioVid Heat Pain Database. Experimental results show that facial response is rare during low intensity pain stimulation and that the proposed measures can successfully identify highly expressive individuals, for whom pain stimuli can be classified reliably, and non-expressive individuals, who may have felt less pain than intended and encoded in labels.

SYSTEM ARCHITECTURE:

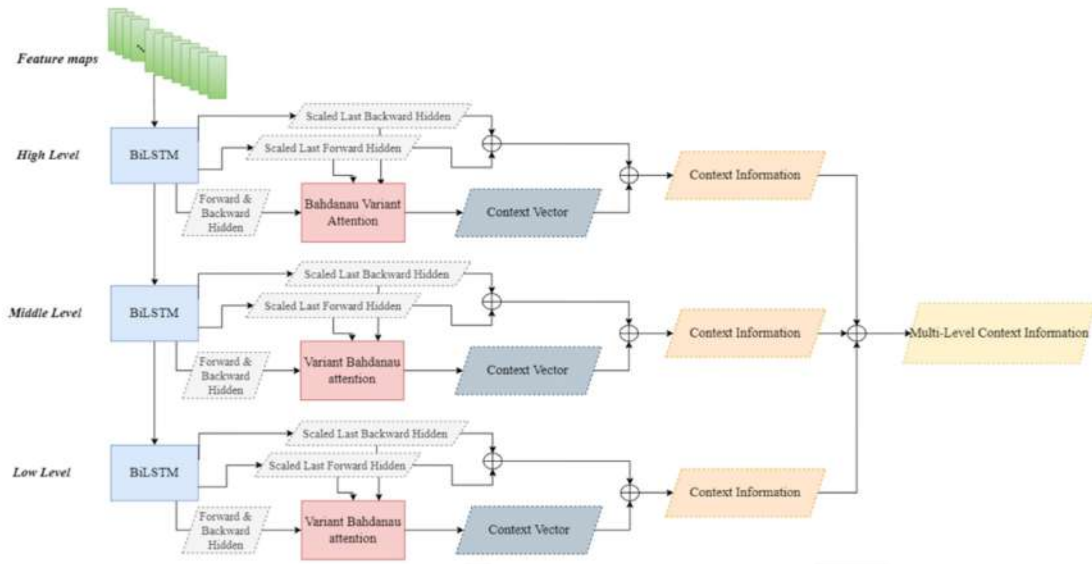


Fig..1 System architecture

DATA FLOW DIAGRAM:

1. The DFD is also called as bubble chart. It is a simple graphical formalism that can be used to represent a system in terms of input data to the system, various processing carried out on this data, and the output data is generated by this system.
2. The data flow diagram (DFD) is one of the most important modeling tools. It is used to model the system components. These components are the system process, the data used by the process, an external entity that interacts with the system and the information flows in the system.
3. DFD shows how the information moves through the system and how it is modified by a series of transformations. It is a graphical technique that depicts information flow and the transformations that are applied as data moves from input to output.
4. DFD is also known as bubble chart. A DFD may be used to represent a system at any level of abstraction. DFD may be partitioned into levels that represent increasing information flow and functional detail.
5. **HARDWARE REQUIREMENTS**
6. The most common set of requirements defined by any operating system or software application is the physical computer resources, also known as hardware, A hardware requirements list is often accompanied by a hardware compatibility list (HCL), especially in case of operating systems. An HCL lists tested, compatible, and sometimes incompatible hardware devices for a particular operating system or application. The following sub-sections discuss the various aspects of hardware requirements.

7. **Architecture –** All computer operating systems are designed for a particular computer architecture. Most software applications are limited to particular operating systems running on particular architectures. Although architecture-independent operating systems and applications exist, most need to be recompiled to run on a new architecture. See also a list of common operating systems and their supporting architectures.
8. **Processing power –** The power of the central processing unit (CPU) is a fundamental system requirement for any software. Most software running on x86 architecture define processing power as the model and the clock speed of the CPU. Many other features of a CPU that influence its speed and power, like bus speed, cache, and MIPS are often ignored. This definition of power is often erroneous, as AMD Athlon and Intel Pentium CPUs at similar clock speed often have different throughput speeds. Intel Pentium CPUs have enjoyed a considerable degree of popularity, and are often mentioned in this category.
9. **Memory –** All software, when run, resides in the random access memory (RAM) of a computer. Memory requirements are defined after considering demands of the application, operating system, supporting software and files, and other running processes. Optimal performance of other unrelated software running on a multi-tasking computer system is also considered when defining this requirement.
10. **Secondary storage –** Hard-disk requirements vary, depending on the size of software installation, temporary files created and maintained while installing or running the software, and possible use of swap space (if RAM is insufficient).
11. **Display adapter –** Software requiring a better than average computer graphics display, like graphics editors and high-end games, often define high-end display adapters in the system requirements.
12. **Peripherals –** Some software applications need to make extensive and/or special use of some peripherals, demanding the higher performance or functionality of such peripherals. Such peripherals include CD-ROM drives, keyboards, pointing devices, network devices, etc.

6. IMPLEMENTATION

MODULES:

- Data exploration: using this module we will load data into system
- Exploring BioVid_coords dataset for understanding data structure and content.
- Processing data with pandas, numpy for reshaping, and dropping columns.
- Normalizing training data using a suitable normalization technique.
- Visualizing data patterns with seaborn and matplotlib for insights.
- Applying label encoding to convert categorical variables into numerical format.
- Selecting relevant features to improve model performance and efficiency.
- Splitting data into train & test: using this module data will be divided into train & test
- Model generation: Model building - Random Forest, CNN + BiLSTM, CNN + BiLSTM + BiGRU, Stacking Classifier.
- User signup & login: Using this module will get registration and login

- User input: Using this module will give input for prediction

Prediction: final predicted displayed

SYSTEM TESTING

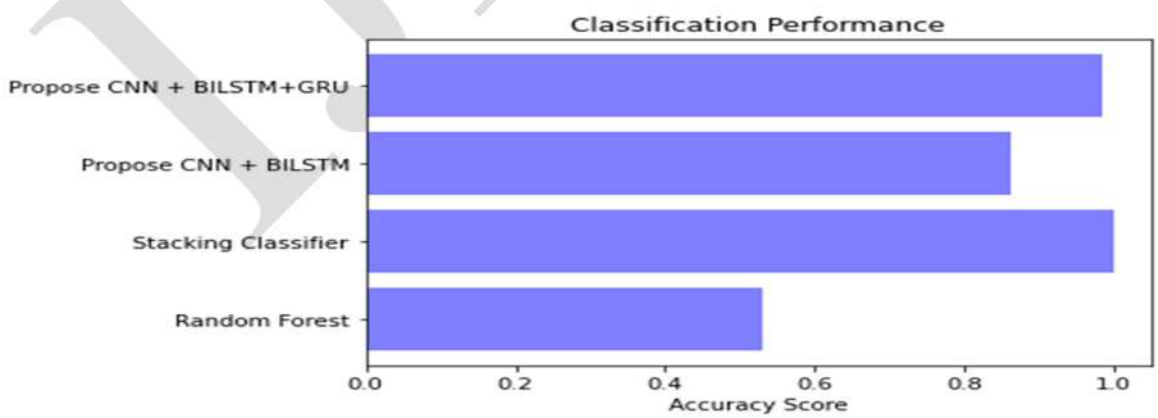
System testing, also referred to as system-level tests or system-integration testing, is the process in which a quality assurance (QA) team evaluates how the various components of an application interact together in the full, integrated system or application. System testing verifies that an application performs tasks as designed. This step, a kind of black box testing, focuses on the functionality of an application. System testing, for example, might check that every kind of user input produces the intended output across the application.

TEST CASES:

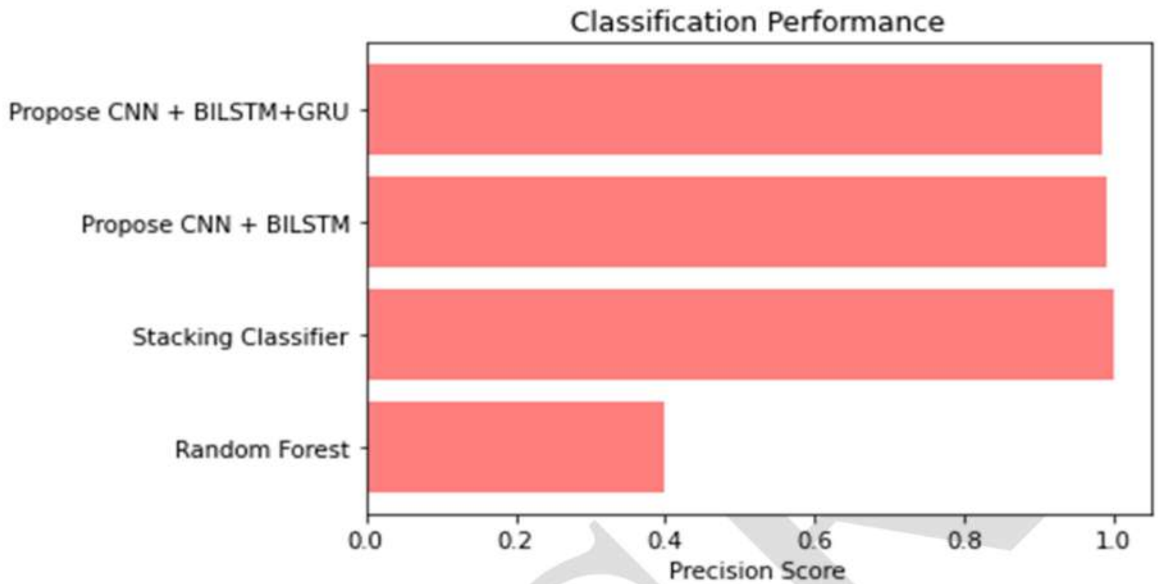
S.NO	INPUT	If available	If not available
1	User signup	User get registered into the application	There is no process
2	User sign in	User get login into the application	There is no process
3	Enter input for prediction	Prediction result displayed	There is no process

RESULTS

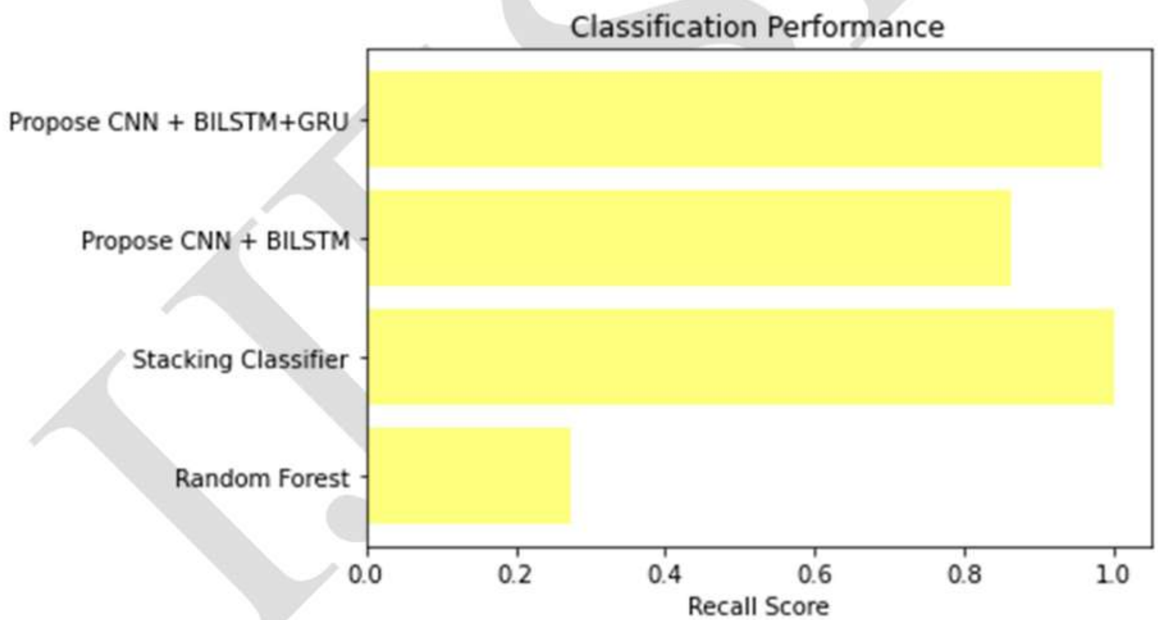
SCREENS:



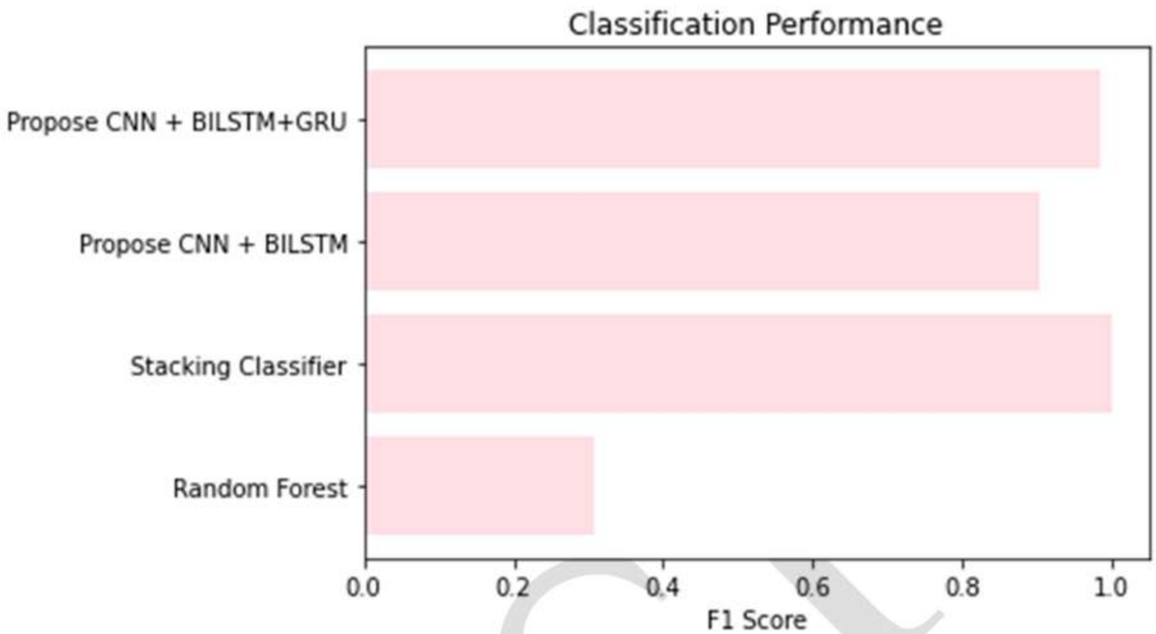
Accuracy Graphs



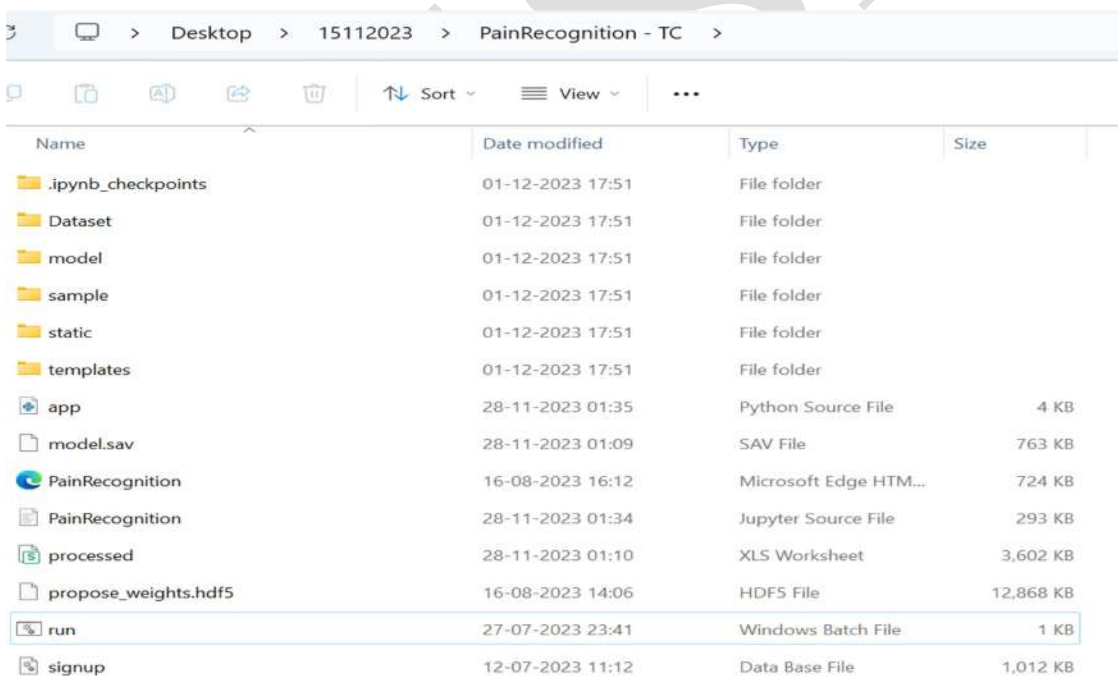
Precision Graphs



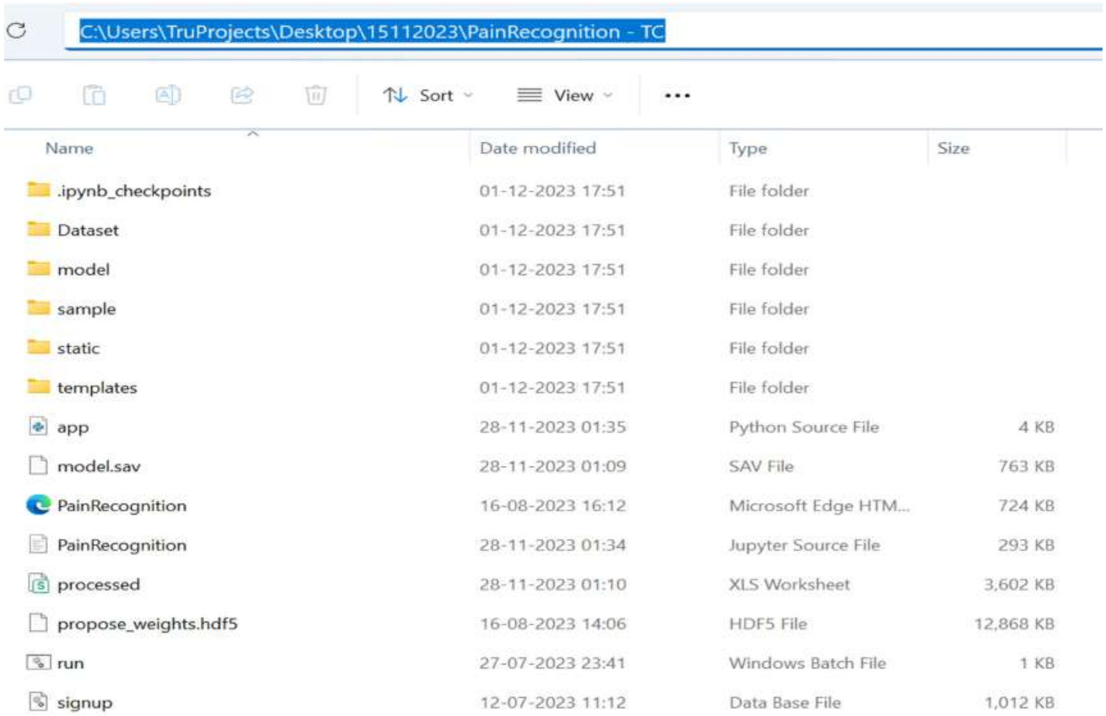
Recall Graphs



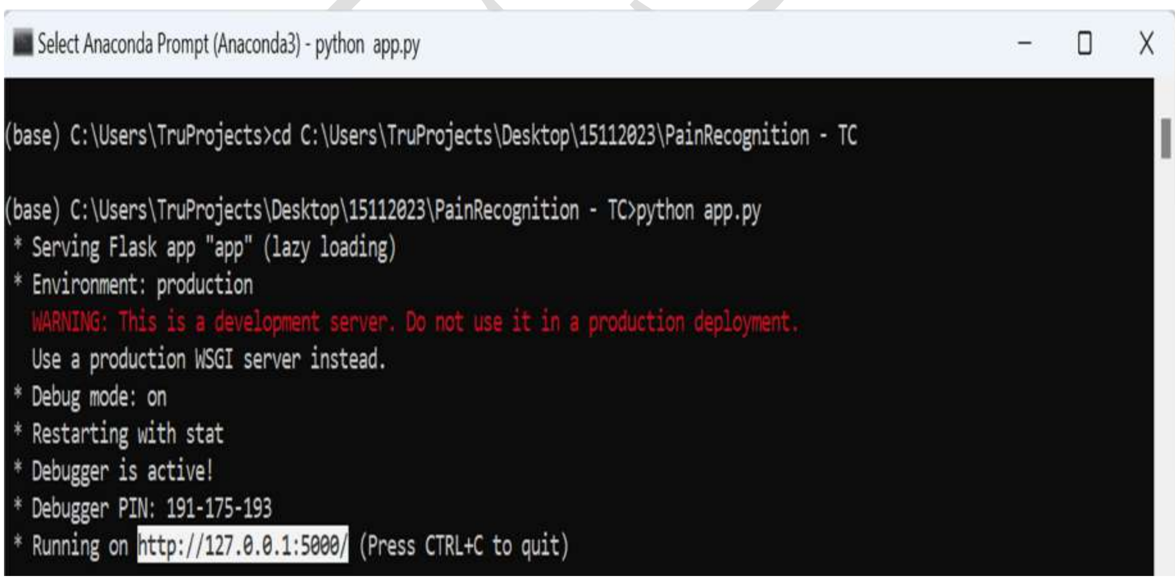
F1 Graphs



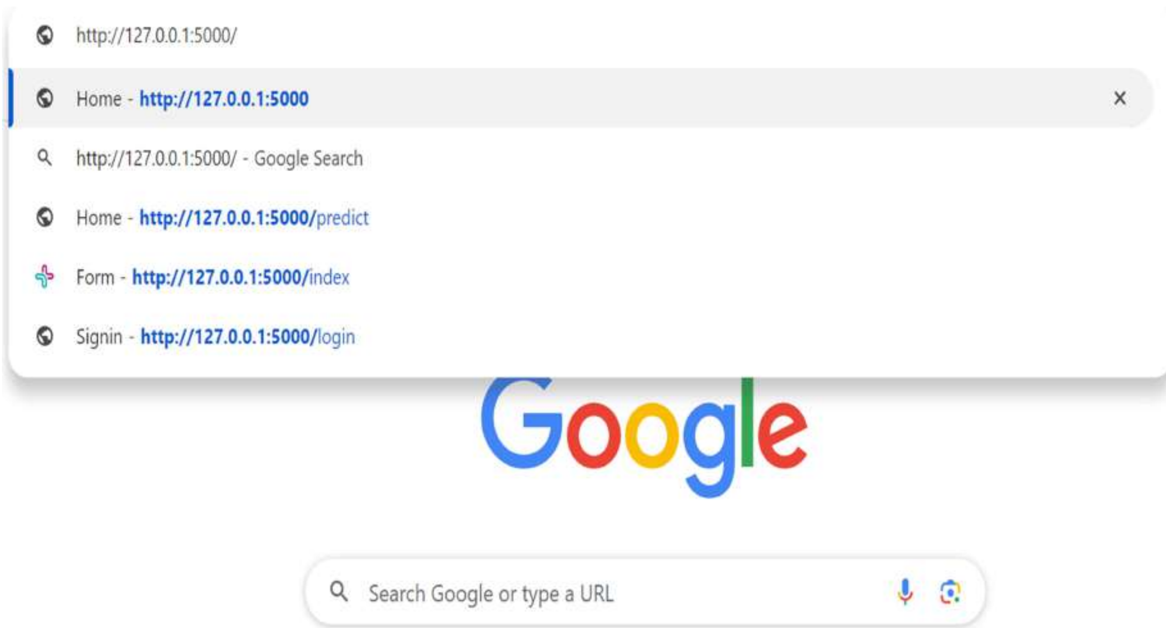
Step 1


C:\Users\TruProjects\Desktop\15112023\PainRecognition - TC
Sort
View
Name
Date modified
Type
Size
.ipynb_checkpoints 01-12-2023 17:51 File folder
Dataset 01-12-2023 17:51 File folder
model 01-12-2023 17:51 File folder
sample 01-12-2023 17:51 File folder
static 01-12-2023 17:51 File folder
templates 01-12-2023 17:51 File folder
app 28-11-2023 01:35 Python Source File 4 KB
model.sav 28-11-2023 01:09 SAV File 763 KB
PainRecognition 16-08-2023 16:12 Microsoft Edge HTM... 724 KB
PainRecognition 28-11-2023 01:34 Jupyter Source File 293 KB
processed 28-11-2023 01:10 XLS Worksheet 3,602 KB
propose_weights.hdf5 16-08-2023 14:06 HDF5 File 12,868 KB
run 27-07-2023 23:41 Windows Batch File 1 KB
signup 12-07-2023 11:12 Data Base File 1,012 KB

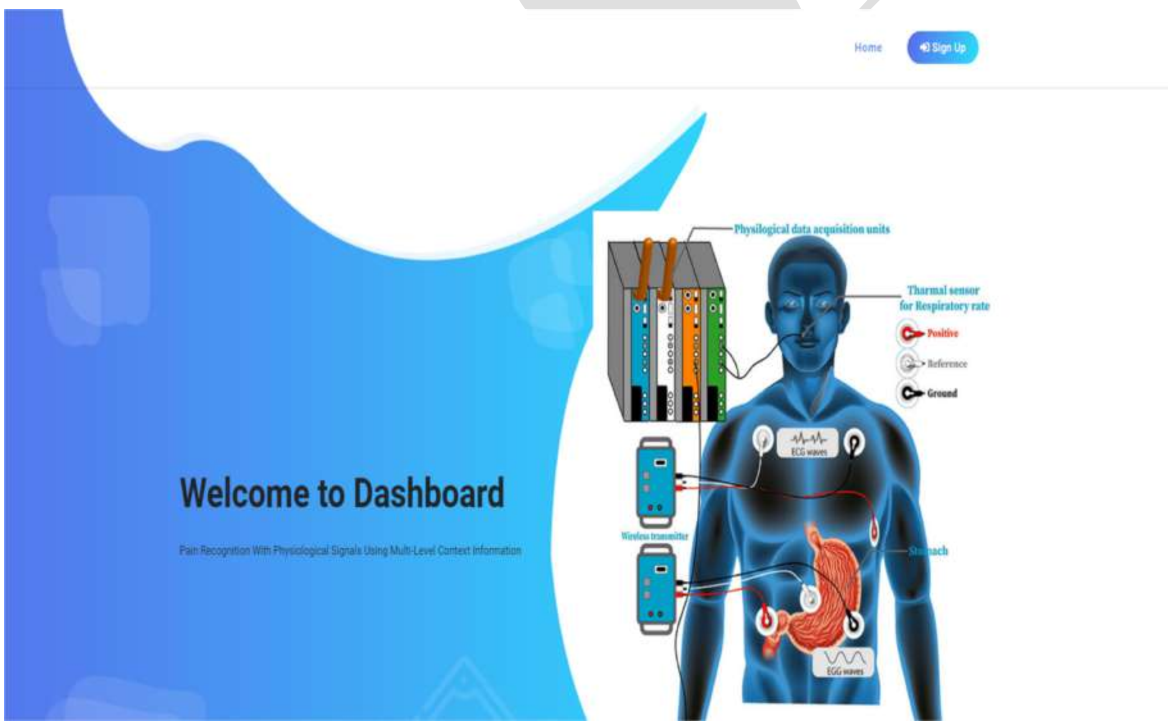
Step 2


Select Anaconda Prompt (Anaconda3) - python app.py
(base) C:\Users\TruProjects>cd C:\Users\TruProjects\Desktop\15112023\PainRecognition - TC
(base) C:\Users\TruProjects\Desktop\15112023\PainRecognition - TC>python app.py
* Serving Flask app "app" (lazy loading)
* Environment: production
WARNING: This is a development server. Do not use it in a production deployment.
Use a production WSGI server instead.
* Debug mode: on
* Restarting with stat
* Debugger is active!
* Debugger PIN: 191-175-193
* Running on http://127.0.0.1:5000/ (Press CTRL+C to quit)

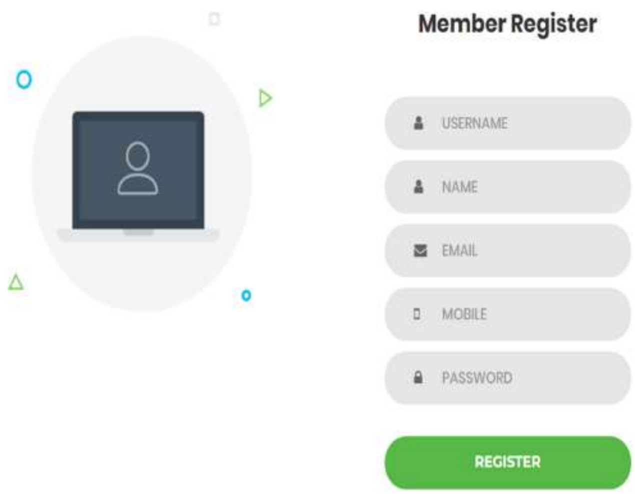
Step 3


http://127.0.0.1:5000/
Home - http://127.0.0.1:5000
http://127.0.0.1:5000/ - Google Search
Home - http://127.0.0.1:5000/predict
Form - http://127.0.0.1:5000/index
Signin - http://127.0.0.1:5000/login
Google
Search Google or type a URL

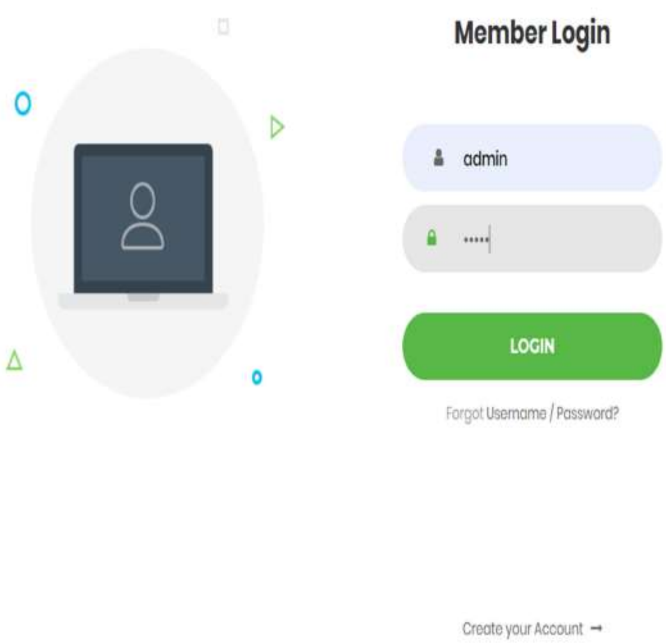
Step 4


Home
Sign Up
Welcome to Dashboard
Pain Recognition With Physiological Signals Using Multi-Level Context Information
Physiological data acquisition units
Tharmal sensor for Respiratory rate
Positive
Reference
Ground
ECG waves
Wireless transmitter
EGG waves

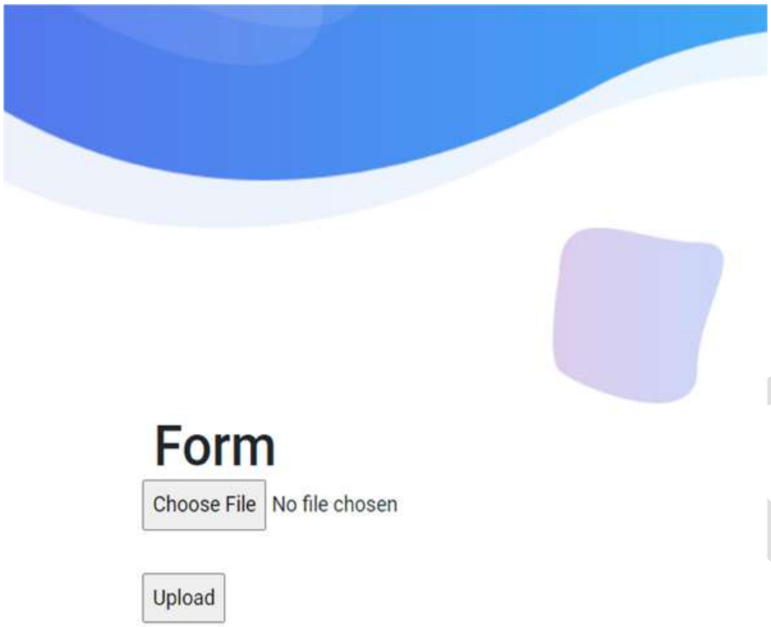
Step 5


Member Register
USERNAME
NAME
EMAIL
MOBILE
PASSWORD
REGISTER

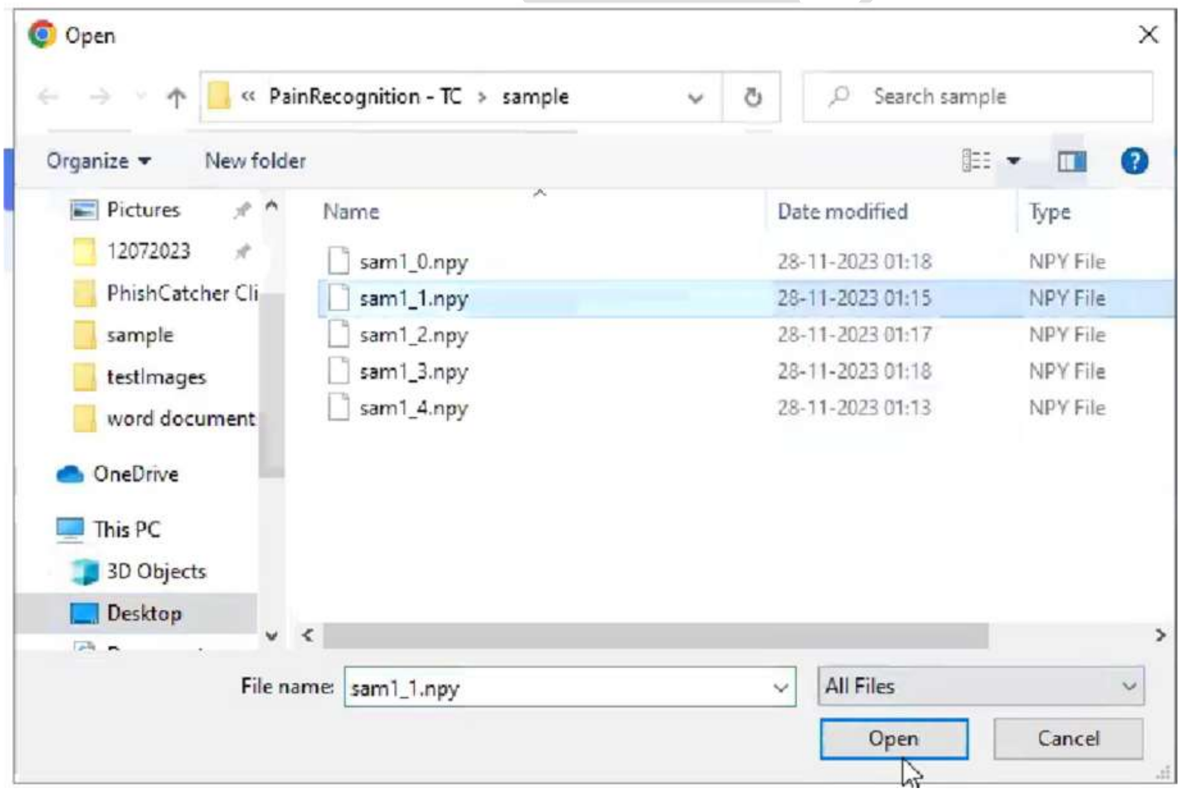
Step 6


Member Login
admin
LOGIN
Forgot Username / Password?
Create your Account

Step 7


Form
Choose File
No file chosen
Upload

Step 8


Open
« PainRecognition - TC › sample
Search sample
Organize ▾
New folder
Pictures
12072023
PhishCatcher Cli
sample
testImages
word document
OneDrive
This PC
3D Objects
Desktop
Name
Date modified
Type
sam1_0.npy 28-11-2023 01:18 NPY File
sam1_1.npy 28-11-2023 01:15 NPY File
sam1_2.npy 28-11-2023 01:17 NPY File
sam1_3.npy 28-11-2023 01:18 NPY File
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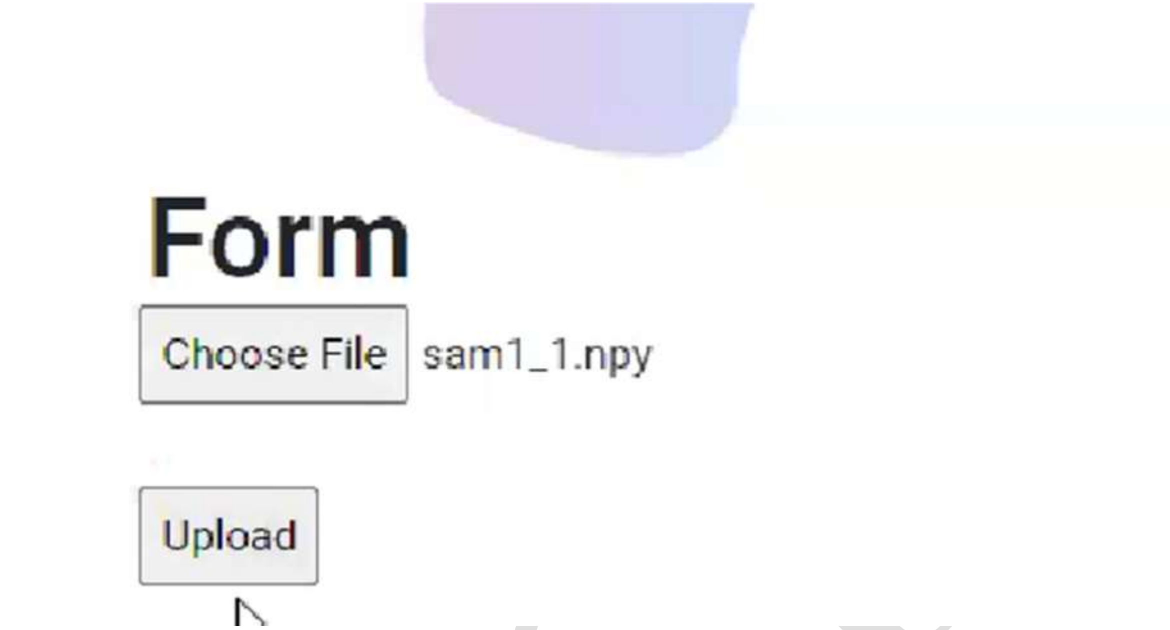
All Files
Open
Cancel

Step 9



Step 10

Step 11

ISSN 2277-2685
IJESR/June-2024/ Vol-14/Issue-2s/234—250
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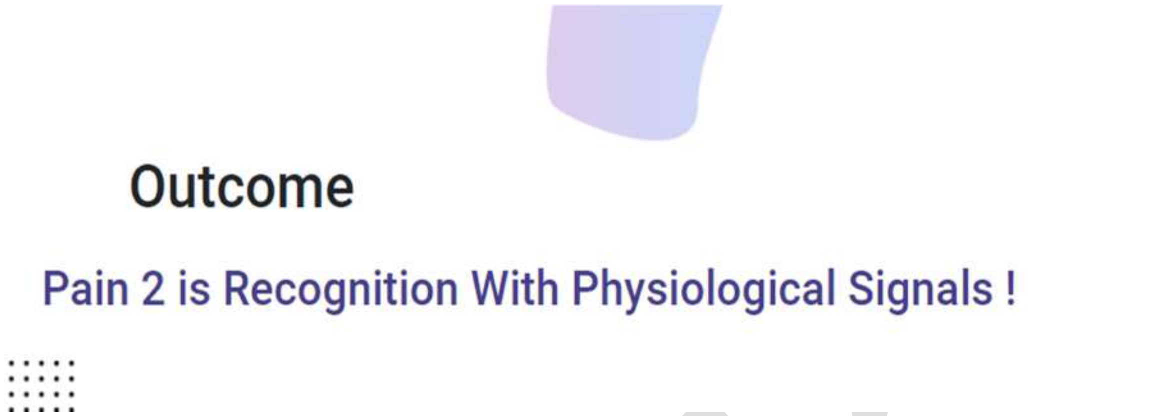
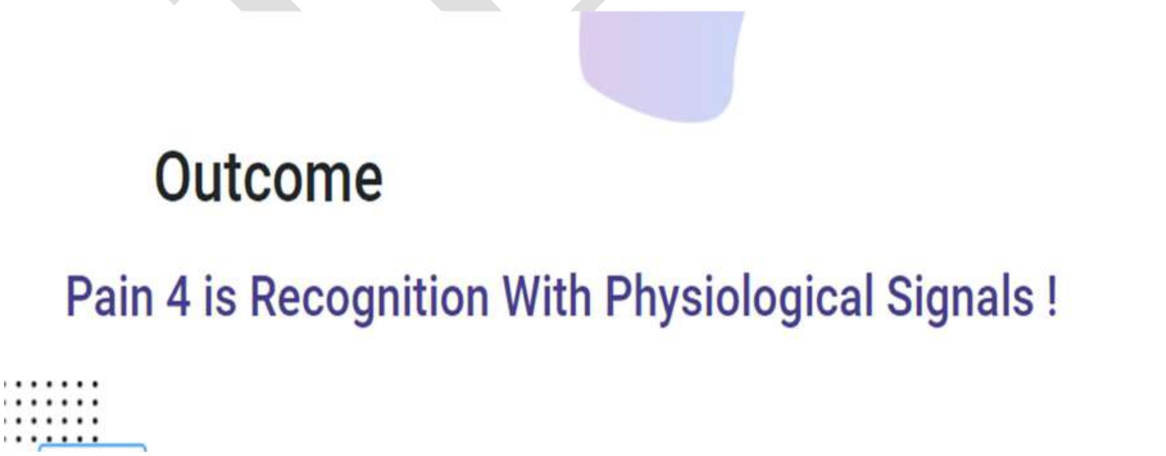
Step 12



Step 13

Step 14



Step 15

CONCLUSION

This paper proposes a deep learning approach based on physiological signals for pain recognition. Our method has the role of feature extraction and classification, completely replacing manual extraction methods that require highly specialized knowledge. We propose multi-level context information explored from hidden sequence information. Specifically, the architecture employs hidden information for the attention mechanism to create the context vector. We combine hidden information and context vector to create the context information. Combining context information at three levels produces multi-level context information. We perform binary classification between baseline and different pain intensities based on Part A of the BioVid Heat Pain database. In addition, we also perform binary classification based on the Emopain 2021 dataset. Our experimental results prove that multi-level context information has more significance than uni-level context information based on Part A of the BioVid Heat Pain database and the Emopain 2021 dataset. Our results demonstrate the great significance of EDA in pain classification. Combining EDA and ECG mostly provides good performance in classification tasks based on Part A of the BioVid Heat Pain database. In summary, the deep learning approach has superior potential to replace previous conventional methods in pain recognition tasks. The exploration of hidden information in the physiological signal sequence provides significant performance for classification tasks.

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