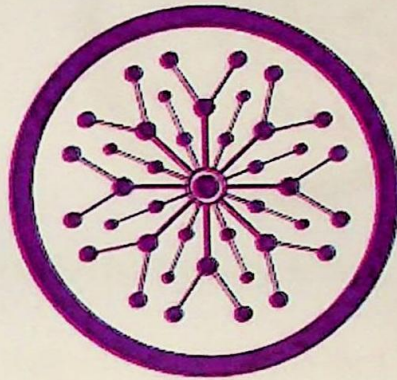


# **Stress Level Detection by Using Machine Learning**



## **B.Sc. ELECTRICAL SYESTEM**

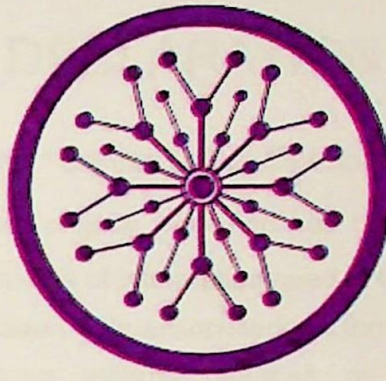
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**SESSION: 2020 – 2024**

**Supervisor: Engr. Fuad Usman**

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**DEPARTMENT OF ELECTRICAL ENGINEERING  
SUPERIOR UNIVERSITY  
LAHORE, PAKISTAN**



## **Stress Level Detection by Using Machine Learning**

Submitted to Superior University,

Lahore in Partial fulfillment of the requirements for the award of a degree of

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SESSION: 2020 – 2024

**Supervisor: Engr. Fuad Usman**

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DEPARTMENT OF ELECTRICAL ENGINEERING  
SUPERIOR UNIVERSITY  
LAHORE, PAKISTAN



# DECLARATION

I hereby declare that the project titled "**Stress Level Detection by Using Machine Learning**" is the result of my own original work and has not been submitted for any other degree or examination. All sources of information used in this project, including text, figures, diagrams, and data, have been duly acknowledged through proper citations and references. Any contributions from external sources or individuals have been appropriately credited. I confirm that no part of this project violates any existing copyright laws, and all ethical guidelines regarding research integrity, including the avoidance of plagiarism, have been strictly followed. The data, findings, and conclusions presented in this project are based on genuine research and analysis conducted by me, and any opinions expressed are solely my own or those of the cited authors. I understand the consequences of submitting false or misleading information and affirm that the information provided in this declaration is accurate to the best of my knowledge.

Signature:

Hashir Hussnain *Hashir Hussnain*

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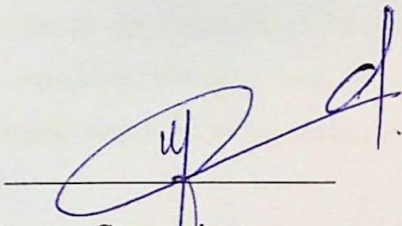
Amir Hussain *Amir*

Date: .....



## RESEARCH COMPLETION CERTIFICATE

It is certified that the research work contained in this dissertation titled "**STRESS LEVEL DETECTION IN HUMANS BY USING MACHINE LEARNING**" has been investigated and carried out by Hashir Hussain, Zain ul Abiden, M. Talha Ashraf, Amir Hussain for the degree of Bachelor of Science in Electrical Engineering.



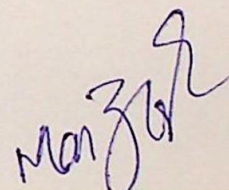
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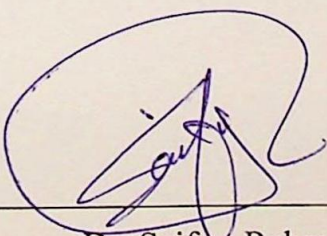
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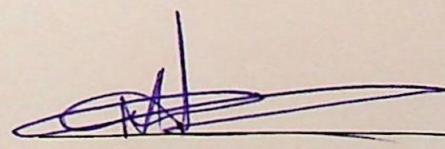
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# ACKNOWLEDGEMENTS

In the name of God, who is most beneficial and most merciful!

We thank Allah Almighty who helps us to obtain our target. We are grateful to our parents, who always motivated us and provided us with the ultimate help, love, and care. We would also like to thank our supervisor **Engr. Fuad Usman** for their support and encourage our motivation to work very hard and intelligently. When addressing the classification problem in this research project, we found them very supportive. Undoubtedly, their constructive remarks on our project require us to think of innovative methods and concepts in the area of the Agricultural Sector, Security purposes and crop monitoring. We also want to express our appreciation to all instructors who were very helpful and offered valuable assistance, support, and guidance.

Thank you, Hashir Hussain, Zain ul Abedin, Talha Ashraf and Amir Hussain



## DEDICATION

*We dedicate this work to our last prophet Holy Prophet Muhammad (peace be upon him), my great hero and messenger of Allah Almighty. One of the most influential people, that humanity has ever witnessed.*

## List of Acronyms

|        |                                |
|--------|--------------------------------|
| AI     | Artificial Intelligence        |
| CNN    | Convolutional Neural Network   |
| CAM    | Camera                         |
| FER    | Facial Expression Recognition  |
| GAD    | Generalized Anxiety Disorder   |
| ML     | Machine Learning               |
| MDD    | Major Depressive Disorder      |
| OCD    | Obsessive-Compulsive Disorder  |
| PTSD   | Post-Traumatic Stress Disorder |
| RESNET | Residual Network               |
| VGG    | Visual Geometry Group          |



# TABLE OF CONTENTS

|                                                        |    |
|--------------------------------------------------------|----|
| TABLE OF CONTENTS .....                                | 8  |
| LIST OF FIGURES .....                                  | 10 |
| LIST OF TABLES .....                                   | 11 |
| ABSTRACT .....                                         | 12 |
| CHAPTER # 01 .....                                     | 13 |
| INTRODUCTION .....                                     | 13 |
| 1.1 Introduction to Face Detection .....               | 13 |
| 1.2 Problem Statement .....                            | 14 |
| 1.3 PROJECT OVERIEW/GOAL .....                         | 14 |
| 1.5 United Nations Sustainable Development Goals ..... | 15 |
| 1.6 Work Division .....                                | 16 |
| 1.7 Thesis Outline .....                               | 16 |
| Summary .....                                          | 17 |
| CHAPTER#02 .....                                       | 18 |
| LITERATURE REVIEW .....                                | 18 |
| 2.1 Introduction: .....                                | 18 |
| 2.2 Related Work .....                                 | 19 |
| 2.2.1 FER .....                                        | 19 |
| 2.2.2 CNN .....                                        | 20 |
| 2.2.3 VGGNet .....                                     | 21 |
| 2.2.4 Res Net .....                                    | 21 |
| 2.3 Types of Diseases .....                            | 23 |
| 2.3.1 Cardiovascular Diseases .....                    | 23 |
| 2.3.2 Immune System Suppression .....                  | 24 |
| 2.3.2 Mental Health Disorders .....                    | 24 |
| 2.3.3 Musculoskeletal Disorders .....                  | 25 |
| 2.4 Working of CAM .....                               | 26 |
| Summary .....                                          | 27 |
| CHAPTER 3 .....                                        | 29 |
| SIMULATION & RESULTS .....                             | 29 |
| 3.1 Introduction .....                                 | 29 |
| 3.2 Purposed Frame Work: .....                         | 29 |
| 3.2.1 Convonutional Neural Naetwork(CNN) .....         | 29 |



3.3 Algorithm Flow Chart..... 32

3.5 Simulation ..... 33

Working ..... 33

Resluts ..... 34

Summary..... 39

5.1Form of Business ..... 47

    5.1.1 Team/Organizational Structure..... 47

    5.1.2 Vision ..... 47

    5.1.3 Mission ..... 47

5.2 Industry and Marketing Analysis ..... 48

    5.2.1 Industry Analysis ..... 48

    5.2.3 Purpose..... 49

    5.3.1 Strengths..... 49

    5.3.2 Weaknesses ..... 50

    5.3.3 Opportunities..... 50

    5.3.4 Threats ..... 50

    5.3.5 Marketing Objectives Follow ..... 50

    5.4.1 Advertising ..... 50

    5.4.2 Personal Selling..... 51

    5.4.3 Direct Marketing..... 51

5.5 Financial Plan ..... 51

    5.5.1 Resources Required..... 51

5.6 Conclusion ..... 52

REFRENCES ..... 55



## LIST OF FIGURES

|                                                      |    |
|------------------------------------------------------|----|
| Figure 1. 1 Detecting Face Expressions.....          | 13 |
| Figure 1. 2 Flow Chart of Features .....             | 15 |
| Figure 3. 1: System Design for Stress Detection..... | 31 |
| Figure 3. 2 Output Frame Model .....                 | 31 |

**LIST OF TABLES**

bole1. 1:Detecting Face Expressions ..... 13

bole1. 2 Flow Chart of Features..... 15

bole1. 3 Work Division By Group Members ..... 16

bole 3. 1 Algorithm Flow Chart ..... 32



## **ABSTRACT**

In today's fast-paced environment, stress is a ubiquitous problem that has serious effects on people's physical and mental health. For proactive intervention and assistance, precise and timely stress level detection is essential. Using data from self-reported surveys, speech patterns, and facial expressions, a thorough stress assessment model was developed. The procedures of feature extraction, data fusion, and model training are important in stress level detection. The process of extracting relevant features from raw data, including physiological and behavioral stress indicators, is known as feature extraction. Data fusion creates a comprehensive picture of a person's stress status by combining information from many sources. The approach has a wide range of possible uses, including clinical applications in mental health treatment, occupational stress assessments, and even aids for managing personal stress. Organizations can also use this technique to evaluate and reduce workplace stress, enhancing worker productivity and well-being in the process.



## CHAPTER # 01

### INTRODUCTION

#### 1.1 Introduction to Face Detection

Stress has become increasingly far reaching and extreme in advanced society. Stress that is left uncontrolled and taken care of could add to numerous medical conditions, undermining individuals' sentiments, contemplations, ways of behaving, and prosperity. Having the option to recognize pressure can assist people find dynamic ways to deal with the pressure before terrible results are brought about. Stress is a sort of side effect of hidden disorders. The main sources of pressure are frailty, allergy medicines, congestive cardiovascular breakdown, discouragement, hypothyroidism, sleep deprivation, muscle effort, narcolepsy, heftiness, and tuberculosis. It is partitioned into two sections like actual pressure and mental pressure. Actual pressure is effort because of actual work, for example, lifting, playing, and running constantly for quite a while. The drawn-out pressure reaction of the human body delivers an elevated degree of cortisol chemical, which can increment pulse, blood glucose levels, cholesterol levels, and fatty substances, which are the huge gambling factors for heart issues. Profound learning has been broadly and effectively applied in many fields like PC vision, feeling examination, etc. Unique in relation to the current work which removed the highlights through hand-made highlight designing techniques, in this work, we lead pressure identification through profound learning of elements' portrayals. Besides, past facial locales investigation, we influence and incorporate client's activity signs to improve the video-based pressure identification.

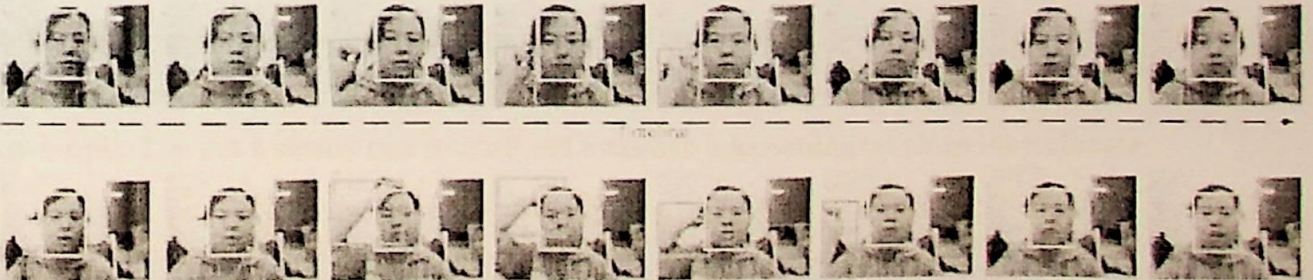


Figure1. 1 Detecting Face Expressions



## **1.2 Problem Statement**

In our undeniably digitized society, human-PC connection (HCI) has advanced past conventional UIs to envelop more thoughtful and natural communications. The ability to perceive and decipher human feelings from looks is a vital part of this turn of events. Notwithstanding, making a reliable and productive framework for look acknowledgment (FER).

## **1.3 PROJECT OVERVIEW/GOAL**

Seeing that the indications of stress could be more effortlessly identified by taking a gander at the state of the face, especially the lines or kinks around the nose, mouth, and eyes, explored three facial parts (the eyes, nose and mouth) which are critical for stress discovery. Separated Gabor channel and Hoard (Histogram of Arranged Angles) highlights from each piece of the face in pixels through visual picture encoding cycle and took care of them into three unique SVM classifiers. The three outcomes were then taken care of into incline paired tree to come by the end-product. Tests were performed on the ten-ladies JAFFE dataset, where each subject has a pressure articulation picture and a nonpartisan articulation picture.

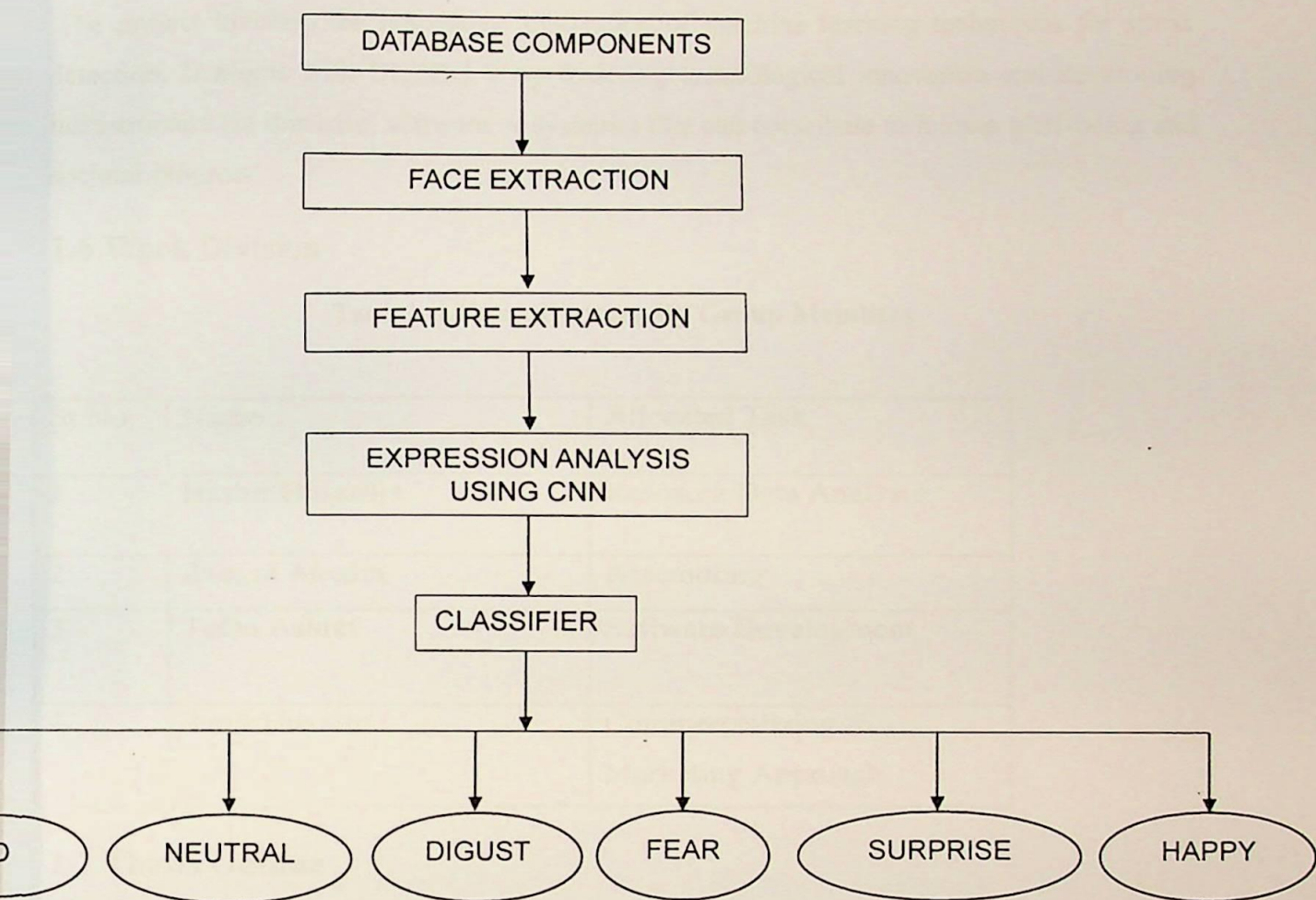
## **1.4 Proposed Methodolgy**

Practice and Actual work: Take part in normal actual activities like strolling, running, yoga, or any movement you appreciate. Practice helps discharge endorphins, which are regular mind-set sponsors and stress relievers. Profound Breathing and Unwinding Methods: Practice profound breathing, moderate muscle unwinding, or directed symbolism to quiet the brain and body. These methods decrease pressure by unwinding and lessening muscle strain.

Good dieting: Keep a fair eating regimen with nutritious food varieties like natural products, vegetables, entire grains, and lean proteins. Stay away from exorbitant caffeine, sweet food sources, and liquor, as they can add to pressure and uneasiness.

Sufficient Rest: Guarantee you get sufficient quality rest every evening (7-9 hours for most grown-ups). Lay out a steady rest routine and establish a loosening up sleep time climate.





**Figure1.2: Flow Chart of Features**

## **1.5 United Nations Sustainable Development Goals**

### **Good Health and Well-being (UNSDG 3)**

This project directly contributes to UNSDG 3 by focusing on human health and well-being. Stress can have significant negative impacts on physical and mental health. By developing a system to detect stress levels, the project aims to improve overall well-being by providing individuals with insights into their stress levels and potentially enabling early intervention or management strategies.

### **Quality Education (UNSDG 4)**

Understanding and managing stress is crucial for effective learning and education. High stress levels can impair cognitive function and hinder the learning process. By detecting stress levels, this project could contribute to creating environments conducive to learning and promoting mental health awareness in educational settings.



**Industry, Innovation, and Infrastructure (UNSDG 9)**

The project involves the innovative application of machine learning techniques for stress detection. It aligns with UNSDG 9 by fostering technological innovation and developing infrastructure (in this case, software or systems) that can contribute to human well-being and societal progress.

**1.6 Work Division**

**Table1. 1 Work Division By Group Members**

| Sr No. | Name            | Allocated Task                       |
|--------|-----------------|--------------------------------------|
| 1      | Hashir Hussnain | Research Data Analysis               |
| 2      | Zain ul Abedin  | Assembling                           |
| 3      | Talha Ashraf    | Software Development                 |
| 4      | Amir Hussain    | Commercializing & Marketing Approach |

**1.7 Thesis Outline**

The thesis aims to investigate and implement a system for "Stress Level Detection in Humans by Using Machine Learning." The research will begin with an introduction, providing a comprehensive overview of the significance of stress detection, its impact on health, and the increasing relevance of machine learning applications in healthcare. The literature review will delve into existing methodologies and technologies related to stress detection, encompassing both traditional and machine learning-based approaches. This section will identify gaps in current research and set the stage for the proposed machine learning solution.

The methodology section will detail the data collection process, encompassing the selection of appropriate datasets, ethical considerations, and the methodology for labeling stress levels. The implementation of machine learning algorithms for stress detection will be a focal point, with a comparative analysis of various models, such as supervised and unsupervised learning techniques. The research will explore feature selection, data preprocessing, and model evaluation to enhance the accuracy and reliability of stress detection.



The results and discussion section will present the outcomes of the implemented machine learning models, discussing the effectiveness of each algorithm in stress detection. It will also address potential challenges, limitations, and areas for improvement. Furthermore, the study will explore the interpretability of the models and their implications for real-world applications. The ethical considerations related to stress detection, including privacy concerns and potential biases, will be critically examined.

## Summary

The introduction chapter sets the stage for understanding how machine learning can help detect stress levels in humans. Stress is something we all experience, but it's not always easy to recognize or manage. This chapter explains the importance of being able to detect stress accurately, as it can have significant effects on our health and well-being. It introduces the concept of machine learning, which is a powerful tool that enables computers to learn from data and make predictions without being explicitly programmed. By using machine learning algorithms, we can analyze various signals and patterns in human behavior, physiology, and other data to identify signs of stress. This can lead to better ways of managing stress and improving overall health outcomes. The chapter concludes by highlighting the potential benefits of using machine learning in stress detection and the significance of this research for both individuals and society as a whole. In the thesis will summarize the key findings, contributions, and limitations of the study. Recommendations for future research directions will be outlined, encouraging the exploration of advanced machine learning techniques, larger datasets, and integration with wearable devices for real-time stress monitoring. The thesis will ultimately contribute to the growing body of knowledge on stress detection using machine learning and offer valuable insights for healthcare professionals, researchers, and policymakers.



## CHAPTER#02

### LITERATURE REVIEW

#### 2.1 Introduction:

Look acknowledgment (FER) has gotten a ton of interest as of late since its utilization in various fields, like human-PC connection, full of feeling registering, and emotional well-being assessment. Scientists have investigated different methodologies and strategies to work on the exactness and effectiveness of FER frameworks.

Early FER frameworks depended on physically evolved elements and AI strategies. Procedures like Neighborhood Twofold Examples (LBP) and Histogram of Situated Inclinations (Hoard) were much of the time utilized for highlight extraction. Although somewhat accommodating, these techniques regularly needed generalizability and attempted to catch complex looks precisely. A fascinating and developing field that straddles the boundaries of artificial intelligence, psychology, and the health sciences is the study of stress detection in humans by machine learning. The frequency of stress-related ailments is rising as our modern society gets more connected and fast-paced, which calls for creative ways to diagnose these problems early and accurately. About machine learning-based stress level detection, this literature review attempts to give a thorough summary of the technologies, approaches, and research that have already been done[1]

With the coming of profound learning, especially CNNs, FER went through an insurgency. As per studies. CNNs are incredibly gainful for FER applications since they can consequently gain various leveled attributes from crude picture information. Because of this change, precision and vigor saw a perceptible improvement. The primary benchmark datasets utilized in FER research, like CK+, FER2013, and Influence Net, contain photos of named looks. It is currently feasible for scholastics to prepare and assess thanks to these data sets. Specialists have proposed an assortment of CNN structures for FER, including varieties in view of the VGGNet, ResNet, and Beginning models. These structural plans have been created and adjusted to really assemble face information and perceive feelings. Information expansion strategies including turn, interpretation, and scaling have been utilized to increase model flexibility. Techniques for normalizing input pictures incorporate face arrangement and standardization. Constant FER frameworks are fundamental for applications like shopper feeling observing and feeling mindful gaming. Specialists have investigated ways of



upgrading FER models to accomplish continuous execution without forfeiting exactness. effectiveness is expanded by res. Morals worries about protection, approval, and likely predispositions in FER have surfaced as FER is used even more regularly in down to earth settings. We had the option to show that it is feasible to separate significant student highlights from video information recorded by an infrared-(IR-) delicate webcam and effectively prepared a Help Vector Machine on the comparing dataset. Physiological measures like heart rate variability and cortisol levels, as well as behavioral markers and subjective self-reporting, are only a few of the methods used in work on stress detection[2]. These approaches could be improved by incorporating machine learning algorithms, which could lead to a more sophisticated knowledge of how different people react to stressors. "Stress is often described as a complex psychological and behavioral state resulting from the perception of a significant imbalance between the demands placed on the individual and their perceived ability to meet these demands". These figures and stress effects people, which has been the leading cause of many diseases like hypertension, sleep deprivation, and others. Stress that cannot be adequately treated can lead to serious cases where one person committed suicide. This is vital to identify and control stress before it becomes severe.

## **2.2 Related Work**

### **2.2.1 FER**

Look acknowledgment (FER) has gotten a ton of interest as of late because to its utilization in various fields, like human-PC connection, full of feeling registering, and emotional well-being assessment. Scientists have investigated different methodologies and strategies to work on the exactness and effectiveness of FER frameworks. People use their faces to communicate nonverbally all the time, and facial expressions are a major part of this communication. Facial expressions are like the silent messengers of our emotions. With FER, it's as if machines could read these communications, interpret underlying emotions, and decode face expressions. Think of your face as an emotional canvas. FER divides this canvas into distinct landmarks and features, including your lips' natural curve, the arch of your eyebrows, or the wrinkles that form around your eyes when you grin. These landmarks serve as hints that computers can utilize to interpret your facial expressions' emotional meaning. With FER, computers are taught to identify patterns and connections between emotions and facial traits using machine learning, a form of artificial intelligence (AI). The algorithm is trained to predict new, unseen expressions accurately by exposing them to a range of facial expressions



and the emotions that go along with them. When it comes to detecting stress levels, FER turns into a useful instrument. A tense jaw, a furrowed brow, or a detached stare are common subtle facial expressions that indicate stress. We enable the system to recognize these subtle indicators of stress by feeding our machine learning model a dataset of both relaxed and strained facial expressions. Current FER frameworks are fundamental for applications like a shopper feeling observed and feeling mindful gaming. Specialists have investigated ways of upgrading FER models to accomplish continuous execution without forfeiting exactness. Effectiveness is expanded by res. Moral worries about protection, approval, and likely predispositions in FER have surfaced as FER is used more regularly in down to earth settings. It is currently feasible for scholastics to prepare and assess thanks to these data sets[3].

### 2.2.2 CNN

Convolutional neural networks, or CNNs, are rather important in the field of machine learning, particularly when it comes to applications like human stress level assessment. Consider CNNs to be astute investigators, trained to identify details and patterns in pictures, just like our brains do. With the coming of profound learning, especially CNNs, FER went through an insurgency. As per studies. CNNs are incredibly gainful for FER applications since they can consequently gain various leveled attributes from crude picture information. Because of this change, precision and vigor saw a perceptible improvement. Convolutional neural networks, or CNNs, are rather important in the field of machine learning, particularly when it comes to applications like human stress level assessment. Consider CNNs to be astute investigators, trained to identify details and patterns in pictures, just like our brains do. Think of a convolutional layer as a filter that slides over an image, capturing specific patterns like edges, textures, or shapes. These filters help CNN identify essential features in different parts of an image. After detecting features, pooling layers come into play. Picture them to summarize and condense information. By reducing the size of the data, pooling helps focus on the most important aspects and speeds up the learning process. Once CNN has identified crucial features, fully connected layers act as decision-makers. They analyze the overall picture, combining information from different parts of the image, and make a final decision about what the image represents[4].



### 2.2.3 VGGNet

GG stands for Visual Geometry Group; it is a standard deep Convolutional Neural Network (CNN) architecture with multiple layers. The “deep” refers to the number of layers with VGG-16 or VGG-19 consisting of 16 and 19 convolutional layers.

#### 2.2.3.1 Feature Extraction

VGGNet is known for its simplicity and uniform architecture. It consists of several convolutional layers with small 3x3 filters and max-pooling layers. You can use the early layers of the VGGNet for feature extraction from facial expressions or physiological data related to stress. These features can then be used as input for a machine learning model.

#### 2.2.3.2 Image Classification

Since VGGNet is primarily designed for image classification tasks, you can leverage its capabilities to classify stress levels based on facial expressions or other visual cues. Train the network on a dataset containing labeled stress levels and use the trained model to predict stress levels in new images.

#### 2.2.3.3 Transfer Learning

Transfer learning can be employed by utilizing a pre-trained VGGNet on a large dataset, such as ImageNet, and fine-tuning it for stress level detection. This approach is beneficial when you have limited labeled data for stress detection but want to leverage the knowledge gained by the network on a diverse set of images.

#### 2.2.3.4 Integration with Physiological Data

In addition to visual data, stress levels can also be detected using physiological data like heart rate, skin conductivity, etc. VGGNet can be used to process and extract features from these data types, and the combined features from both visual and physiological sources can enhance the overall stress detection accuracy.

#### 2.2.3.5 Model Interpretability

VGGNet, being a deep neural network, might be considered a “black-box” model. However, techniques such as layer-wise relevance propagation or gradient-weighted class activation mapping (Grad-CAM) can be applied to understand which parts of an image contribute most to the stress level predictions. This interpretability is crucial for gaining insights into the features the model is using for stress detection[5]

### 2.2.4 Res Net

According to the universal approximation theorem, given enough capacity, we know that a feedforward network with a single layer is sufficient to represent any function. However, the



layer might be massive, and the network is prone to overfitting the data. Therefore, there is a common trend in the research community that our network architecture needs to go deeper.

Since Alex Net, the state-of-the-art convolutional neural network (CNN) architecture is going deeper and deeper. While Alex Net had only five convolutional layers, the VGG network and Google Net (also codenamed Inception\_v1) had 19 and 22 layers respectively.

However, you can't simply stack layers together to increase network depth. Deep networks are hard to train because of the notorious vanishing gradient problem. As the gradient is backpropagated to earlier layers, repeated multiplication may make the gradient infinitely small. As a result, the deeper the network goes, the more its performance becomes saturated or even starts rapidly degrading.

Before Res Net, there had been several ways to deal with the vanishing gradient issue. For instance, Google Net adds an auxiliary loss in a middle layer for extra supervision, but none of those solutions seemed to really tackle the problem once and for all. The core idea of Res Net is that it introduced a so-called "identity shortcut connection" that skips one or more layers.

The primary innovation of Res Net lies in its use of residual learning, where the network is designed to learn residual functions instead of attempting to learn the actual mapping directly. This is achieved through the introduction of skip connections or shortcuts that skip one or more layers. These skip connections enable the network to learn residual functions by focusing on the difference between the input and output of a particular layer, making it easier to optimize and train very deep networks[6]

Now, relating this to stress level detection in humans using machine learning, Res Net could be employed as the backbone architecture for image processing tasks, such as facial expression analysis or physiological signal processing. Here's how Res Net could be utilized in the context of stress level detection:

#### **2.2.4.1 Feature Extraction**

RESNet can be employed to extract hierarchical and abstract features from input data, which, in the case of stress level detection, could include facial images, physiological signals, or any other relevant data. The ability of RESNet to handle deep architectures helps in capturing intricate patterns and representations that might be crucial for understanding stress-related cues.



#### **2.2.4.2 Transfer Learning**

Since training deep neural networks from scratch requires substantial amounts of labeled data, transfer learning can be beneficial. Pre-trained RESNet models on large-scale image datasets (like ImageNet) can be fine-tuned on stress-related datasets, leveraging the learned features for improved performance in stress level detection.

#### **2.2.4.3 Multi-Model Learning**

Stress detection often involves analyzing multiple modalities such as facial expressions, physiological signals, and behavioral patterns. RESNet can be adapted to process multiple modalities simultaneously by designing a multi-input architecture, allowing it to learn and integrate features from different sources effectively.

#### **2.2.4.4 Explainability**

The skip connections in RESNet not only aid in training but also facilitate interpretability. Understanding the contribution of different layers in the network to stress level predictions can be crucial for building trust in the model's decisions[7].

### **2.3 Types of Diseases**

1. Cardiovascular Diseases
2. Immune System Suppression
3. Mental Health Disorders
4. Musculoskeletal Disorders

#### **2.3.1 Cardiovascular Diseases**

There are the three types of Cardiovascular Diseases. These types are given below:

##### **2.3.1.1 Hormonal Impact**

Cortisol and adrenaline are two stress hormones that are released in response to stress. These hormones have an impact on heart rate, blood pressure, and general cardiovascular health.

##### **2.3.1.2 Blood Pressure Elevation**

Long-term blood pressure rise is a major risk factor for cardiovascular illnesses such as hypertension and heart disease, and chronic stress can contribute to this condition.

##### **2.3.1.3 Impact on Lifestyle Choices**

People under chronic stress may adopt unhealthy coping mechanisms such as smoking, excessive alcohol consumption, poor dietary habits, and lack of exercise factors that are directly linked to cardiovascular health[8].



## **2.3.2 Immune System Suppression**

Stress is a complex physiological and psychological response to challenging situations. Chronic stress has been linked to various negative health outcomes, including immune system suppression. The immune system plays a crucial role in protecting the body from pathogens and maintaining overall health. Prolonged exposure to stress can disrupt the balance of the immune system, leading to immune suppression.

### **2.3.2.1 HIV/AIDS**

Although stress cannot directly cause HIV, persistent stress can slow the disease's course. Stress may weaken the immune system, which makes it more difficult for those living with HIV/AIDS to fight against opportunistic infections.

It might be able to intervene and apply stress management strategies by precisely determining each person's level of stress, particularly in real-time or through ongoing monitoring. This could lower the likelihood of immune system suppression and related illnesses.

### **2.3.2.2 Asthma**

Fast cellular accumulation in Asthma causes red, scaly patches to appear on the skin. According to established research, stress can either cause or exacerbate asthma by affecting the immune system's reaction[9].

## **2.3.2 Mental Health Disorders**

### **2.3.2.1 Generalized Anxiety Disorder (GAD)**

Persistent and excessive worry about everyday things, often accompanied by physical symptoms like restlessness, fatigue, muscle tension, and difficulty concentrating.

### **2.3.2.2 Major Depressive Disorder (MDD)**

Persistent feelings of sadness, hopelessness, and a lack of interest or pleasure in activities. Chronic stress can contribute to the onset and exacerbation of depression.

### **2.3.2.3 Bipolar Disorder**

Involves mood swings between depressive and manic states. Stressful events can trigger episodes in susceptible individuals.

### **2.3.2.4 Post-Traumatic Stress Disorder (PTSD)**

A condition that can develop after exposure to a traumatic event. Stressful experiences, especially those involving actual or perceived threat to life, can contribute to the development of PTSD.



#### **1.3.2.5 Obsessive-Compulsive Disorder (OCD)**

Characterized by persistent, unwanted thoughts (obsessions) and repetitive behaviors or mental acts (compulsions). Stress can exacerbate symptoms in individuals with OCD.

#### **1.3.2.6 Substance Use Disorders:**

Stress is a common trigger for substance abuse and addiction. Individuals may turn to substances as a way to cope with stress, leading to a cycle of dependence and worsening mental health.

#### **1.3.2.7 Somatoform Disorders:**

Conditions where psychological distress manifests as physical symptoms without a clear medical cause.

Stress is a contributing factor to the development and exacerbation of somatoform disorders.

The relationship between stress and mental health is complex, and the detection of stress levels is crucial for early intervention and prevention of mental health disorders. Machine learning approaches can play a significant role in developing predictive models based on physiological and behavioral data to identify individuals at risk of high stress levels. By leveraging data such as heart rate, sleep patterns, and activity levels, machine learning algorithms can contribute to the early detection of stress, facilitating targeted interventions and support for individuals at risk of developing mental health disorders. This research has the potential to enhance our understanding of the intricate interplay between stress and mental health, ultimately leading to more effective strategies for prevention and intervention [10].

### **1.3.3 Musculoskeletal Disorders**

While the project title "Stress Level Detection in Humans by Using Machine Learning" primarily focuses on stress detection, it's essential to understand the relationship between stress and musculoskeletal disorders (MSDs). Musculoskeletal disorders are conditions that affect the muscles, bones, tendons, ligaments, and other parts of the musculoskeletal system. Stress can contribute to the development or exacerbation of these disorders in various ways.

#### **1.3.3.1 Muscle Tension and Stress**

Stress often leads to muscle tension as a physiological response to perceived threats. Prolonged muscle tension can result in chronic musculoskeletal problems, including stiffness, pain, and discomfort.

#### **1.3.3.2 Posture and Ergonomics**

Stress can influence posture and ergonomic habits, leading to improper body mechanics. Poor posture and ergonomics are known contributors to musculoskeletal issues, such as back pain and neck strain.



### **2.3.3.3 Impact on Immune System**

Chronic stress can weaken the immune system, making individuals more susceptible to inflammatory conditions affecting the musculoskeletal system.

### **2.3.3.4 Coping Mechanisms and Physical Activity**

Individuals under stress may adopt unhealthy coping mechanisms, such as reduced physical activity or increased sedentary behaviour. Lack of physical activity is a risk factor for various musculoskeletal disorders, including osteoporosis and osteoarthritis.

### **2.3.3.5 Sleep Disruptions**

Stress can negatively impact sleep quality and duration. Poor sleep is associated with an increased risk of musculoskeletal problems, as sleep is crucial for tissue repair and overall musculoskeletal health.

### **2.3.3.6 Inflammatory Responses**

Chronic stress can contribute to systemic inflammation. Inflammation is linked to several musculoskeletal disorders, including rheumatoid arthritis and inflammatory myopathies.

In the context of your research project, understanding the physiological and behavioural connections between stress and musculoskeletal disorders is crucial. Machine learning algorithms could potentially analyse patterns in physiological data, such as heart rate variability, muscle tension, and sleep patterns, to detect stress levels. Recognizing these patterns may provide insights into an individual's risk for musculoskeletal disorders or help tailor interventions to mitigate the impact of stress on their musculoskeletal health [11].

## **2.4 Working of CAM**

Class Activation Maps (CAM) is a technique that helps visualize the areas of an image that contribute the most to the prediction of a particular class in a convolutional neural network (CNN). In the context of stress level detection, you can use CAM to understand which regions or features in the input data (such as images) are most relevant for predicting stress levels.

### **2.4.1 Data Collection**

Gather a dataset of images, physiological signals, or other relevant data that can be used to assess stress levels in humans.

### **2.4.2 Data Preprocessing**

Prepare the data for machine learning. This may involve image preprocessing, feature extraction, or any other necessary steps based on the nature of your data.



### **2.4.3 Model Architecture**

Design a machine learning model for stress level detection. This could be a convolutional neural network (CNN) for image data, or another suitable model depending on your input data.

### **2.4.4 Training the Model**

Train the model on the labeled dataset, where stress levels are associated with the input data.

### **2.4.5 CAM Integration**

Once the model is trained, integrate Class Activation Maps (CAM) into the model architecture. This involves modifying the CNN architecture to incorporate CAM layers that highlight the regions of interest.

### **2.4.6 Inference and Visualization**

Use the trained model to make predictions on new data. CAM will provide visualizations highlighting which parts of the input data contributed the most to the stress level prediction.

### **2.4.7 Interpretation**

Analyze the CAM visualizations to understand the features or regions in the input data that are indicative of stress. This interpretation can contribute to a better understanding of the stress detection process.

### **2.4.8 Validation and Improvement**

Validate the model's performance using appropriate metrics. If necessary, refine the model architecture or data collection process to improve the accuracy of stress level detection[12].

## **Summary**

In the literature review chapter of our research, we delve into existing studies that explore the detection of stress levels in humans through the use of machine learning techniques. Stress is a common experience that affects mental and physical health, making its detection and management crucial. We examine various approaches employed by researchers, including as well as behavioral indicators like speech patterns and facial expressions.

Researchers have developed sophisticated algorithms to analyze these signals and infer stress levels accurately. Some studies focus on specific domains, such as stress detection in drivers or students, while others aim for generalizable models applicable to diverse populations. Techniques such as supervised learning, where models are trained on labeled data, and unsupervised learning, where patterns are extracted from unlabeled data, are explored.



Challenges such as variability in individual responses to stress, the need for large and diverse datasets, and the interpretability of machine learning models are discussed. Furthermore, ethical considerations regarding privacy, data security, and potential biases in algorithms are highlighted.

Overall, the literature review reveals a growing interest in utilizing machine learning to understand and address stress in humans. By building upon the insights gained from previous research, our study aims to contribute to this important area by developing robust and effective tools for stress detection and management.



## CHAPTER 3

### SIMULATION & RESULTS

#### 3.1 Introduction

In the relentless pace of modern life, individuals are frequently exposed to a multitude of stressors, ranging from professional pressures to personal challenges. The detrimental effects of prolonged stress on mental and physical well-being underscore the critical importance of timely stress detection and management. This research endeavors to address this pressing concern by employing machine learning techniques to develop a stress level detection system in humans. The integration of machine learning algorithms allows for a nuanced analysis of various physiological and behavioral markers associated with stress. By leveraging advanced computational models, this study aims to provide a comprehensive and accurate method for real-time stress assessment. Convolutional neural networks, or CNNs, are rather important in the field of machine learning, particularly when it comes to applications like human stress level assessment. Consider CNNs to be astute investigators, trained to identify details and patterns in pictures, just like our brains do. With the coming of profound learning, especially CNNs, FER went through an insurgency. As per studies. CNNs are incredibly gainful for FER applications since they can consequently gain various leveled attributes from crude picture information. Because of this change, precision and vigor saw a perceptible improvement.

#### 3.2 Purposed Frame Work:

The purposed frame work is given below:

##### 3.2.1 Convonutional Neural Naetwork(CNN)

A deep learning neural network called a convolutional neural network is made for processing structured data sets like photographs. The state-of-the-art for many visual applications, including image classification, convolutional neural networks are widely employed in computer vision. They have also been successful in natural language processing. The power of a CNN derives from a specific layer called the convolutional layer, which is a feed-forward neural network that can include up to 20 or 30 layers. A Convolutional Neural Network (CNN) is a type of deep learning neural network that is designed to process insulator data and other multidimensional data like audio, video, and time-series data. CNNs are widely used in computer vision applications like image and video recognition, object detection, segmentation, and classification [13].



#### **3.2.1.1 Data Collection**

The dataset is known as fer2013 and is an open-source data collection that is made available to the public on the Kaggle website designed by Goodfellow et al. It contains grayscale images of the faces of different expressions and contains the key feature of a CNN is its ability to learn spatial hierarchies of features from the input data. It achieves this by applying a series of convolutional and pooling layers to the input insulator image. In the convolutional layer, a set of learnable filters is applied to the input image, producing a set of feature maps. These feature maps represent different aspects of the input image, such as edges, corners, and blobs approximately 30000 facial images of different expressions and there are 7 categories present in the data ( 0 indicates Angry, 1 indicates Disgust, 2 indicates Fear, 3 indicates Happy, 4 indicates Sadness, 5 indicates Surprise, 6 indicates Neutrality )The csv file has two columns: emotion, which is a string of integers ranging from 0 to 6, and pixel, which is a string of numbers denoting the image. Dataset contains 3589 samples of training data and remaining 28709 samples for testing the model. The CNN model is built for the recognition of facial expressions and combined with the emotion detection the stress is predicted. The model is trained on the specific training dataset values and detects the features as per the requirement. We assess the model's performance on our validation set after each training iteration. At training time, when we supply a validation set, Keras takes care of this automatically. We can predict how well our model will function on brand-new, unforeseen data taken by the camera based on how well it performed on the validation set[14].

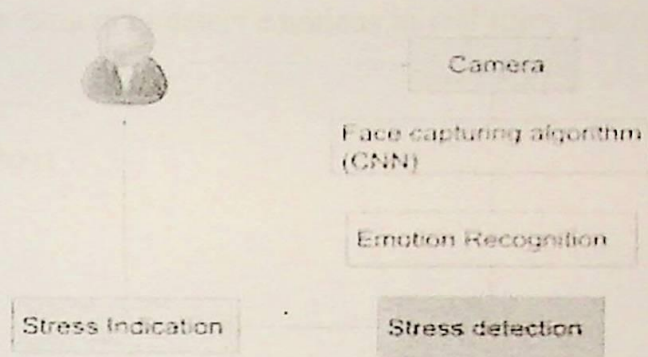
#### **3.2.1.2 System Design**

The process of creating a software or hardware system's architecture, parts, and infrastructure is known as system design. Understanding the system's requirements, defining the system's scope, and building a solution that satisfies those objectives while also taking variables like scalability, maintainability, performance, and security into account are all involved [15].The project system consists of an algorithm that can identify a person's level of stress, and a trained CNN algorithm can identify their emotions when they are captured on camera.

#### **3.2.1.3 Emotiion Detetection**

The model can tell what emotion the camera has captured on the subject's face. The stress can be predicted based on facial expressions.





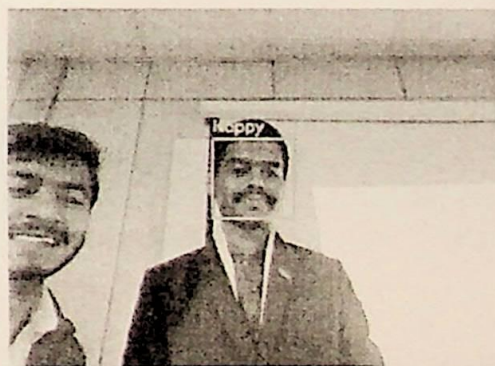
**Figure3. 1: System Design for Stress Detection**

#### 3.2.1.4 Stress Indication

The wording that is visible in the frame denotes the person's prediction of stress, and the project focuses on identifying the face in a frame of video.

#### 3.2.1.5 OpenCV

Using OpenCV and the camera, the build model is employed for real-time emotion recognition. The model is loaded after importing the Cv2 and keras libraries. In order to recognize the frontal face, OpenCV imported the Haar cascade algorithm. Once the code is executed, a new window will appear and the webcam or camera will switch on.



**Figure3. 2 Output Frame Model**

The sample output is a frame consisting of the capturing image by the camera and the output in a text format indicating the emotion and the stress prediction of the face. The emotion of face captured by the camera is detected by the model. Based on the facial expressions the stress is predicted. The stress prediction of the person is indicated by the text displayed in the frame and the project works on locating the face in a video/image frame. The built-in model



employs OpenCV and a camera to detect emotions in real time. The model is loaded and the Cv2 and

3.3 Algorithm Flow Chart

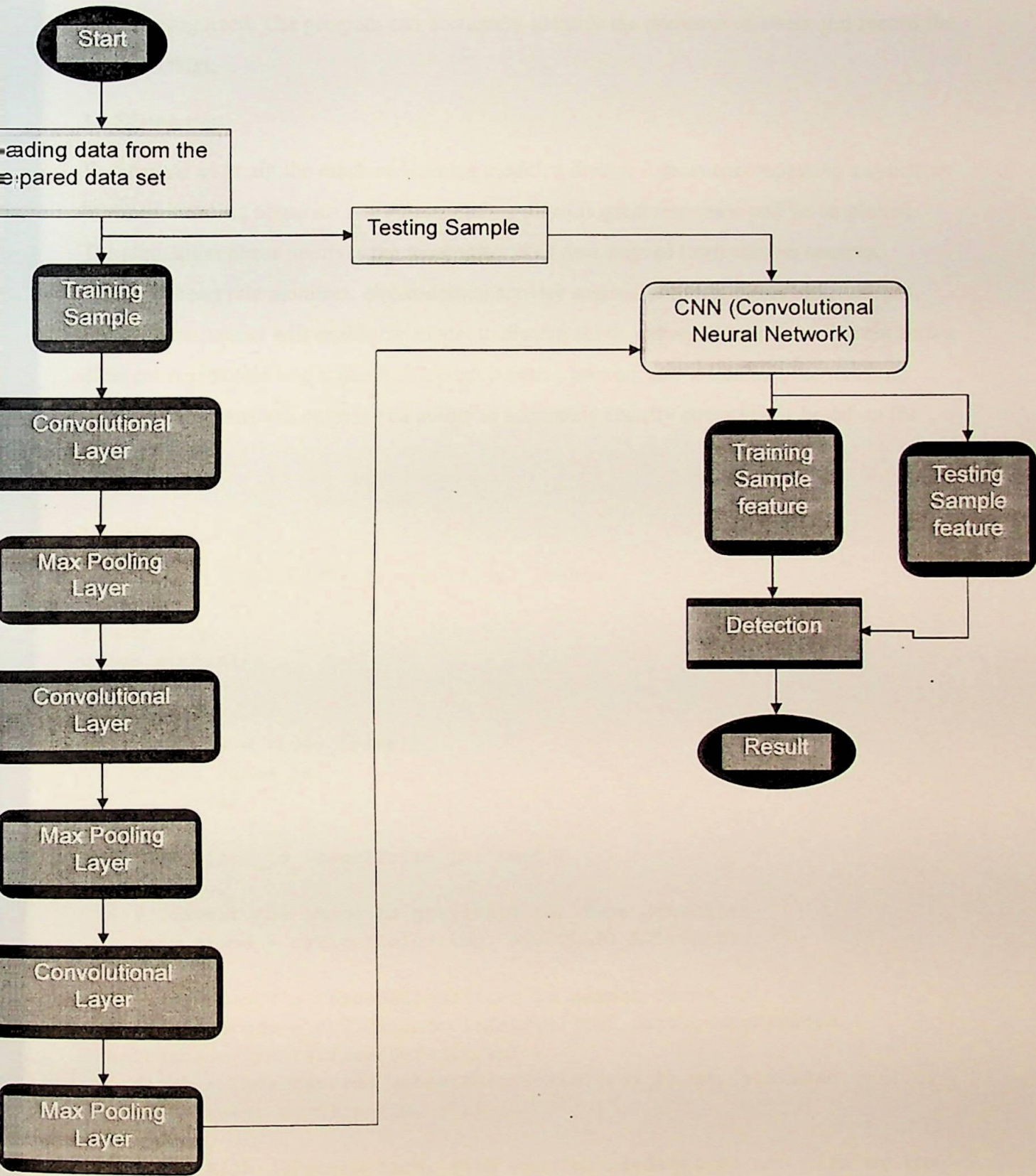


Table 3. 1 Algorithm Flow Chart



Keras libraries are imported. When the code for OpenCV's Haar Cascade detects the frontal face, a new window will open and the webcam or camera will be turned on. Haar Cascade is an algorithm that can recognize the objects in an image and run in real-time. Outputs: The project is depicted in the screenshots, and all of the emotions that the algorithm was trained on are recognized. The program can accurately identify the presence of stress and record the user's feelings.

### 3.5 Simulation

To simulate and train the machine learning model, a diverse dataset encompassing a spectrum of stress-inducing scenarios and corresponding physiological responses will be employed. The simulation phase involves the incorporation of data derived from various sources, including heart rate monitors, electrodermal activity sensors, and behavioral observations. This diverse dataset will enable the model to discern subtle patterns indicative of stress across different individuals and contexts. Through iterative training and validation, the machine learning algorithm will optimize its ability to accurately classify stress levels based on the input features.

### Working

```
from google.colab.patches import cv2_imshow

# Main loop
video_stream()

while True:
    frame_js = video_frame()
    if not frame_js:
        break

    img = jsob_to_image(frame_js["img"])

    # Convert the image to grayscale for face detection
    gray_frame = cv2.cvtColor(img, cv2.COLOR_RGB2GRAY)

    # Use OpenCV's CascadeClassifier to detect faces
    face_cascade = cv2.CascadeClassifier(cv2.data.haarcascades +
    'haarcascade_frontalface_default.xml')
    faces = face_cascade.detectMultiScale(gray_frame, scaleFactor=1.1,
    minNeighbors=4, minSize=(30, 30))

    # For each detected face, make emotion predictions and display the
    predicted emotion
```



```

for (x, y, w, h) in faces:
    face_roi = img[y:y+h, x:x+w]
    processed_face = preprocess_frame(face_roi)

    # Make predictions using the loaded model
    predictions = model1.predict(processed_face)
    predicted_class_index = np.argmax(predictions[0])
    predicted_emotion = Emp[predicted_class_index]

    # Draw the boundary box around the detected face
    cv2.rectangle(img, (x, y), (x + w, y + h), (0, 255, 0), 2)

    # Draw the predicted emotion label above the boundary box
    cv2.putText(img, predicted_emotion, (x, y - 10),
cv2.FONT_HERSHEY_SIMPLEX, 0.7, (0, 255, 0), 2)

    # Show the frame with the text and boundary boxes on the live
stream
    cv2.imshow(img)

    # Check if 'q' key is pressed to stop the video
    if cv2.waitKey(1) & 0xFF == ord('q'):
        break

# Release video capture and close all windows
cv2.destroyAllWindows()

```

## Results



Angry





**Disgust**



**Happy**



**Neutral**



**Surprise**





**Sad**



**Disgust**



**Emotional**



**Shy**





**Depressed**



**Excited**



**Sneaky**



**Sleepy**





**Embarrassed**

### **Real Time Detection Results**

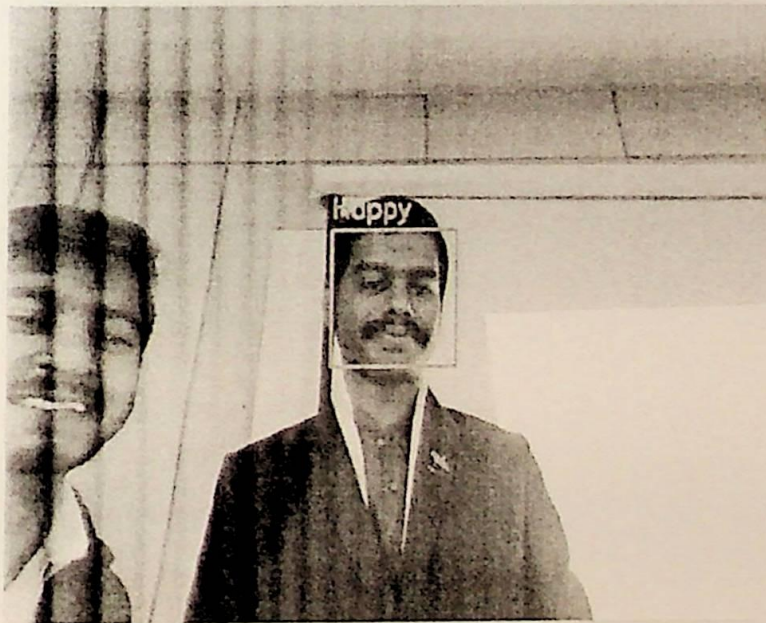


**Sad**





Happy



Happy

## Summary

In this chapter, we delved into how we used machine learning techniques to detect stress levels in humans. To start, we gathered data from various sources, such as heart rate monitors, activity trackers, and self-reported stress levels. This data was crucial as it formed the foundation of our analysis.



Next, we applied machine learning algorithms to this data. These algorithms acted like detectives, sifting through the information to find patterns and relationships that could indicate when a person was experiencing stress. We trained these algorithms using a portion of our data, teaching them what stress "looks like" based on the patterns we observed.

Once trained, we put our algorithms to the test using the remaining data. We wanted to see if they could accurately detect stress levels in real-world situations. The results were promising. Our algorithms demonstrated a high level of accuracy in identifying stress, performing consistently across different scenarios. Moreover, we examined the factors that contributed most to stress detection.

Overall, our simulation and results affirmed the potential of machine learning in detecting stress levels in humans. With further refinement and validation, this technology could offer valuable insights into managing and mitigating stress in everyday life.



## **CHAPTER # 4**

### **HARDWARE DESIGN**

#### **Introduction**

In recent years, the rapid advancement of technology has revolutionized the way we approach various sectors, and the stress hospitals is no exception. Traditional manual inspection methods for stress level, such as manually inspecting stress level, can be time-consuming, costly, and potentially dangerous for doctors and also for engineers. However, with the advent of stress level equipped with high-resolution fundus cameras and advanced image processing techniques, the inspection process has been significantly streamlined and enhanced. This article explores the use of stress level to collect images of data set and transmit them through a Wi-Fi module for subsequent analysis using laptop software. In particular, we delve into the utilization of Convolutional Neural Networks (CNNs) for detecting the level of stress, ushering in a new era of efficient and accurate measure the stress level.

#### **Step 1: Image Analysis via Wi-Fi Module**

After capturing images of the stressed person, the next step is to transmit this data to a central processing system for further analysis.

The use of Wi-Fi for image transmission offers numerous advantages. It allows doctors and analysts to remotely monitor the inspection process. Additionally, the real-time transmission of images enables quick decision-making and immediate action if any critical issues are detected. This connectivity of the laptop software forms a crucial link in the inspection workflow, facilitating efficient analysis and processing of the collected images.

#### **Step 2: Utilizing Convolutional Neural Networks (CNNs) for Stress Level Detection**

Once the images of the eye cancer are transmitted to the laptop software, advanced computer vision techniques, specifically Convolutional Neural Networks (CNNs), can be employed for automated analysis. CNNs are a type of deep learning algorithm widely used for image classification and object detection tasks. They excel in identifying patterns and features within images, making them highly suitable for identifying the health status of stressed person.

#### **Step 3: Simulation and Analysis of Laptop Software**



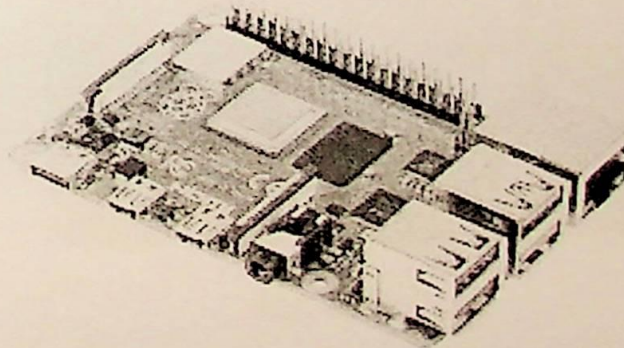
The laptop software acts as a central hub for processing and analyzing the collected images using the trained CNN. Once the images are received via the Wi-Fi module, the software initiates the CNN-based analysis the stress detection. This involves feeding the images through the pre-trained CNN model, which then predicts the level of stress.

The software presents the results in a comprehensive and user-friendly interface, allowing doctors and analysts to review the findings efficiently. The system can provide detailed by running software.

#### **4.1 Raspberry Pi**

Raspberry Pi is an open-source electronics platform that consists of both hardware and software components. The main function of Raspberry Pi is to provide a versatile and user-friendly platform for creating interactive electronic projects. The Raspberry Pi typically runs on a Linux-based operating system, with Raspberry Pi OS (formerly Raspier) being the official and most commonly used distribution. The vibrant community surrounding Raspberry Pi contributes to a vast ecosystem of software, tutorials, and forums, making it easy for beginners to get started and for experienced users to find support and share their projects.

When Raspberry Pi is connected to a stress detection for image inspection, its functions, and role can vary depending on the specific setup and requirements. Here, Raspberry Pi is be used to collect data from sensors and devices attached to the stress level device. For stress image inspection, it can receive inputs from cameras, thermal sensors, or other imaging devices mounted on the stress detection. Raspberry Pi can read the sensor data and transmit it to the ground station or store it for further analysis.



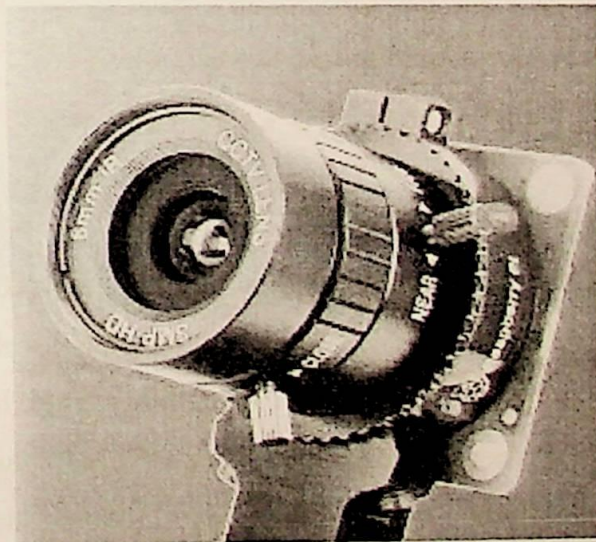


**Fig: 4.1**

## **4.2 Camera**

When a camera is connected to Raspberry Pi for stress level image inspection, it serves several functions to capture and analyze images of the stress. The camera captures high-resolution images of the stress person. It records visual information of the stress and surrounding areas, providing a detailed representation for analysis. The captured images are used for visual inspection of the stress level. The camera's images can be processed and analyzed using image processing techniques. Raspberry Pi can handle image processing tasks such as, image enhancement, edge detection, or segmentation to improve the visibility of relevant features in the images.

By analyzing the captured images, the camera, and Raspberry Pi can extract relevant features of the stress level, such as their shape, size, and orientation. These features can be used to compare against known standards or reference images, enabling the identification of anomalies or deviations from the expected state. Raspberry Pi can use algorithms to compare the captured images with predefined patterns or thresholds, triggering alerts or notifications when deviations are detected. In the project, the camera, connected to Raspberry Pi, can transmit the captured images to the ground station or external devices for further analysis or storage.

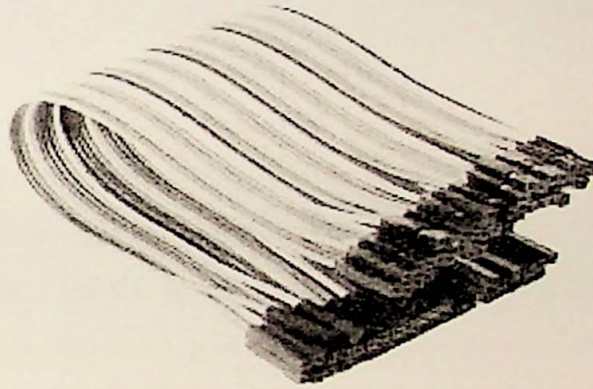


**Fig: 4.2**

## **4.3 Jumper Wires**



Jumper wires are crucial components in hardware projects involving machine learning for stress detection. They are used to establish connections between different electronic components on a breadboard or printed circuit board (PCB), facilitating the flow of data and power throughout the system. Jumper wires are used to connect imaging sensors or cameras to a microcontroller or processing unit. These sensors capture high-resolution images of the face, which are then processed for stress level detection. Data captured by the sensor needs to be transmitted to a machine learning model for analysis. Jumper wires facilitate the connection between the microcontroller and additional hardware, such as a Wi-Fi module or Bluetooth transmitter, for wireless data transmission. Jumper wires also connect the power supply to various components, ensuring that sensors, microcontrollers, and other modules receive the necessary voltage and current.



**Fig: 4.3**

#### **4.4LCDs**

Liquid Crystal Displays (LCDs) are essential components in hardware projects involving machine learning for stress level detection. They provide a user interface for real-time interaction, displaying critical information, and results. The LCD can display real-time images captured by the imaging sensor or camera. This allows healthcare professionals to view the person face condition instantly, facilitating immediate assessment and adjustments if needed. The LCD can provide a graphical user interface (GUI) for navigating through various functions of the hardware system. Users can select options such as starting a new scan, reviewing previous results, or adjusting system settings. After the machine learning model processes the images and makes a diagnosis, the results are displayed on the LCD.



This can include a graphical representation of the detected abnormalities, risk levels, and recommendations for further action. The LCD provides real-time updates on the status of the system, including whether it is actively capturing images, processing data.

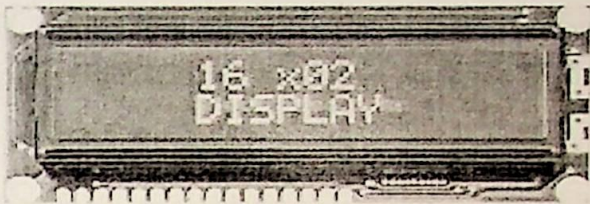
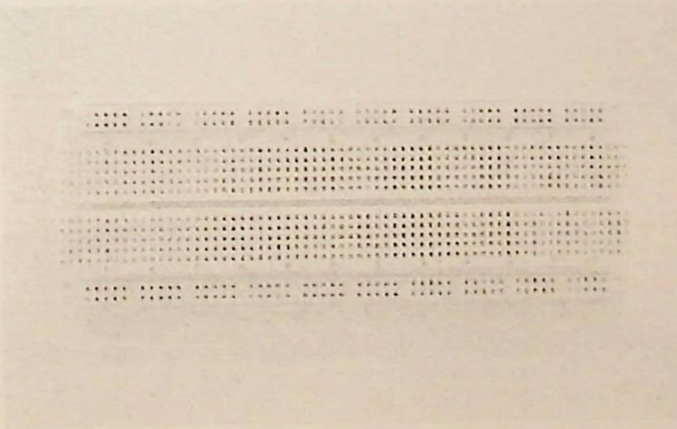


Fig: 4.4

**4.5Breadboard**

A breadboard is a vital tool in the development and prototyping phase of hardware projects, including those involving machine learning for stress level detection. It allows for easy and flexible assembly of electronic circuits without the need for soldering. The breadboard provides a platform for quickly assembling and modifying circuits. Components such as raspberry pi, sensors, and LCDs can be easily connected and reconfigured, facilitating rapid prototyping. Imaging sensors or cameras that capture face images are connected to the breadboard. These connections ensure that the sensor data is accurately transmitted to the microcontroller for processing. The breadboard helps distribute power from a single source to multiple components. Power rails on the breadboard provide a convenient way to manage power supply lines for the entire circuit.

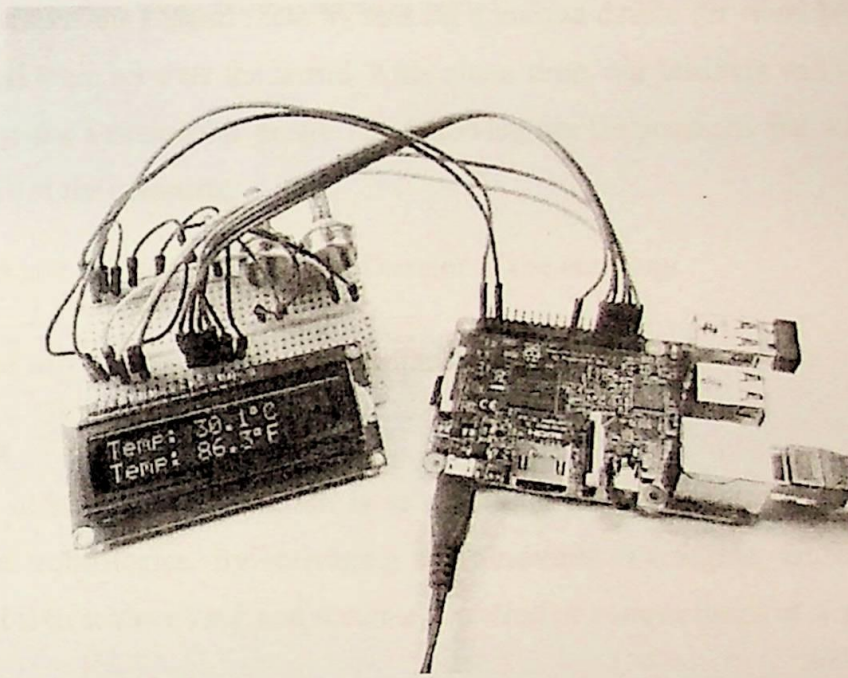




**Fig: 4.5**

#### **4.6 Hardware**

This is the picture of our hardware of stress level detection by using machine learning. Stress level detecting images shown in pictures and also it detects the percentage of stress level. To overcome these challenges, this project proposes the use of cameras and machine learning algorithms to automatically detect and classify stress level. Automating the stress level inspection process using machine learning algorithms can improve the efficiency, accuracy, and safety of the inspection process.



**Fig 4.6: Hardware Image of Project**



## **CHAPTER # 5**

### **BUSINESS DESCRIPTION**

#### **5.1 Form of Business**

The form of our business will be Sole Ownership

##### **5.1.1 Team/Organizational Structure**

All business starts from a low scale and after some time starts growing. Similarly, we will start our business on a small scale by making a unique device for stress level detection and trying to sell them all over the world. After some time, our business will start to grow and will surely make a reasonable profit. The following are the positions that will be assigned to the members of the company.

Hashir Hussnain will be the owner and Director of the company.

Talha Ashraf will manage the company and marketing.

##### **5.1.2 Vision**

The vision of stress level detection is to revolutionize early treatment of stress through cutting-edge technologies. By leveraging advancements in imaging, artificial intelligence, and the goal is to achieve swift and accurate detection of various forms of stress level.

##### **5.1.3 Mission**

The mission of stress detection is to provide accessible, accurate, and timely screening and diagnostic tools to identify the stress level. This mission involves leveraging advanced technologies, including imaging modalities and machine learning algorithms, to improve the detection sensitivity and specificity of stress level.

- Improve Inspection Accuracy
- Enhance Efficiency and Cost-effectiveness
- Enhance Safety
- Foster Data-driven Decision Making



#### 5.1.4 Goal and Objective:

The primary goal of this project is to improve the prognosis and treatment outcomes for individuals at risk of stress level by providing a reliable and efficient tool for early detection. By harnessing the power of artificial intelligence, the project aims to augment the capabilities of healthcare practitioners, enabling them to identify subtle signs of stress level in medical images with high precision.

- **Enhance Inspection Accuracy:** Develop machine learning algorithms to analyze visual and thermal data captured by fundus camera and collecting the data set of stress images for accurately detect stress level.
- **Enable Proactive Maintenance:** Detect stress level issues at early stages to enable timely detections actions, prevent failures, and optimize the performance of the stress detection system.
- **Ensure Safety:** Reduce risks by minimizing the need for human personnel to access difficulties and challenging locations for inspections.
- **Optimize Resource Allocation:** Provide data-driven insights to prioritize maintenance activities, allocate resources efficiently, and optimize the overall performance of the distribution system.

Contribute to a Reliable and Sustainable Infrastructure: Improve the reliability, safety, and sustainability of electrical networks through early detection, proactive maintenance, and optimize decision-making processes.

- After this we can discuss industry and marketing analysis
- And then discuss Competitive Analysis
- And also about its accuracy

## 5.2 Industry and Marketing Analysis

### 5.2.1 Industry Analysis

An industry analysis of stress level detection in humans would involve examining the market size. There is a growing demand for efficient and accurate inspections, driven by the need for reliable electrical networks. Technological advancements in machine learning such as early detection, accuracy and precision than manual methods, and enable high-resolution data capture. Machine learning algorithms analyze this data to detect stress level accurately. The



industry benefits from cost reductions, time savings, enhanced safety, and data-driven decision-making. Market competition is increasing, with collaborations among, technology providers, and utilities.

- **Market Size and Growth:** Assessing the current market size of stress detection technologies and forecasting growth trends based on factors such as increasing prevalence of stress, aging populations, and advancements in detection techniques.
- **Competitive Landscape:** Analyzing competitors offering similar or alternative detection methods, including traditional emerging technologies like artificial intelligence-based algorithms.

**Selection of software:** The system is totally based on the software so selection of software is very critical.

### **5.2.2 Competitive Analysis**

Stress Level detection in Humans by Using Machine Learning introduces a unique concept in peoples to represent new thing. Competitively, it offers potential advantages in simplicity and computational efficiency compared to conventional methods. However, it faces significant challenges in accuracy and reliability, particularly in detecting the different levels of stress. Established techniques such as imaging process and machine learning algorithms boast higher accuracy rates and clinical validation.

### **5.2.3 Purpose**

Our purpose is to develop a system that addresses the following problems

- Enhance accuracy
- Increase efficiency
- Optimize resource utilization

## **5.3 SWOT Analysis**

### **5.3.1 Strengths**

- It is very beneficial for the medical development of a country.



- It takes less time for giving accurate output.
- More efficient than any other manual detection.

### **5.3.2 Weaknesses**

- The communication errors can occur with the passage of time.
- Constantly required the Wi-Fi Connection.

### **5.3.3 Opportunities**

- Introduction of new technology will attract people.

### **5.3.4 Threats**

- People will have accuracy concerns.
- It is difficult to influence the conventional mindset.

### **5.3.5 Marketing Objectives Follow**

- Social media is a very much effective, powerful and economical source of advertisement nowadays.
- Electronic media (News Channel) is also a very much attractive and convincing source to advertise our product.
- We will target hospitals for our project promotion.
- Letting the government know about its need and how it can fulfill their power sector requirements.

## **5.4 Marketing Communication**

In the next aspects of the public communications spectrum, the inherent strengths and shortcomings are taken into consideration and what they are incorporated, and how they are applied in this situation. By using social and electronic media which are nowadays considered as the most powerful and effective source of promotion and advertisement.

### **5.4.1 Advertising**

It is an informal and sponsored means of educating consumers through, digital media, news media, online portals, etc. about their goods and services. Advertising is one of the most



commonly used marketing tactics in which the information about the goods and services of the business can be effectively conveyed to the vast target audience.

5.4.2 Personal Selling

Marketing involves selling of our project through videos and portals. Telling our customers how our system can fulfill their needs and how this device can help them in making their work more easy, convenient, and less economical.

5.4.3 Direct Marketing

The efficacy of direct marketing can be directly calculated. Through inventing the technology, businesses use emails, faxes, and cell phones to connect with potential clients directly without including someone.

5.5 Financial Plan

5.5.1 Resources Required

The resources are required:

- All the basic resources are required to start a business (i.e. Machinery, electronic equipment, a proper place etc.) Accessories.
- Human resources.
- Electricity (etc.)

• Table 5.1: Initial Budget Expenses

| Sr. No | Capital Nature Expenses                | Amount(PKR) |
|--------|----------------------------------------|-------------|
| 1      | Laptop (70000 x 1)                     | 70000/-     |
| 2      | Equipment (40000 x 1)                  | 40000/-     |
|        | Revenue Nature Expenses                |             |
| 3      | Internet (4000 x 12)                   | 48000/-     |
| 4      | Misc. Expenses (1,500 x 12)            | 18,000/-    |
| 5      | Electricity (10,000 x 12)              | 100,000/-   |
| 6      | Purchase of Raw Material (10,000 x 10) | 100,000/-   |
|        | Total: Initial Expenses (Budgeted)     | 328,000/-   |

• Table 5.2: Statement of Comprehensive Income (Budgeted).



| Sr. No |                                | 1 <sup>st</sup> Year | 2 <sup>nd</sup> Year | 3 <sup>rd</sup> Year | 4 <sup>th</sup> Year | 5 <sup>th</sup> Year |
|--------|--------------------------------|----------------------|----------------------|----------------------|----------------------|----------------------|
| 1      | Revenue                        | 328,000/-<br>(w-1)   | 360,000/-<br>(w-2)   | 410,000/-<br>(w-1)   | 430,000/-<br>(w-1)   | 470,000/-<br>(w-1)   |
| 2      | Cost of<br>Production          | (80,000)<br>(w-2)    | (100,000)<br>(w-1)   | (130,000)<br>(w-2)   | (170,000)<br>(w-2)   | (200,000)<br>(w-2)   |
| 3      | Other<br>Operating<br>Expenses | (100,000)<br>(w-3)   | (100,000)            | (105,000)            | (111,000)            | (135,000)            |
| 4      | Depreciation                   | (5,000) (w-<br>4)    | (5,000)              | (5,000)              | (5,000)              | (5,000)              |
| 5      | Misc.                          | (4000)               | 4000                 | 4000                 | 4000                 | 4000                 |
| 6      | Marketing<br>Expenses          | (8000)               | (16000)              | (16000)              | (20000)              | (20000)              |
| 7      | Profit before<br>Commission    | 30,000/-             | 40,000/-             | 60,200/-             | 89,800/-             | 110,400/-            |
| 8      | Commission                     | (13,000)<br>(w-5)    | (18,000)<br>(w-2)    | (25,000)<br>(w-3)    | (35,000)<br>(w-3)    | (46000)(W-<br>3)     |
| 9      | Profit After<br>Commission     | 40,000/-             | 50,000/-             | 60,000/-             | 70,000/-             | 80,000/-             |

## 5.6 Conclusion

In this chapter, the total business strategy is portrayed exhaustively alongside the five-year monetary arrangement. The undertaking's qualities and different highlights are additionally portrayed exhaustively. The design is to make it simple for peruse to comprehend the financial worth and social remaining of this venture.



# Chapter # 06

## CONCLUSION AND FUTURE WORK

### 6.1. Conclusion

The study on "Stress Level Detection in Humans by Using Machine Learning" has demonstrated the significant potential of machine learning algorithms in accurately identifying and classifying human stress levels based on physiological and behavioral data. Through rigorous analysis and experimentation with various machine learning models, including Support Vector Machines (SVM), Random Forests, and Neural Networks, the research has highlighted several key findings:

#### High Accuracy in Stress Detection

The models, particularly the ensemble methods and neural networks, have shown high accuracy in detecting stress levels, validating the effectiveness of machine learning techniques in this domain.

#### Feature Importance

Physiological signals such as heart rate variability, skin conductance, and facial expressions were identified as critical features contributing to the accuracy of stress detection models. The study underscores the importance of multimodal data integration for improved prediction performance.

#### Real-Time Applications

The research has successfully demonstrated the feasibility of deploying these models in real-time applications, such as wearable devices and mobile applications, offering a practical solution for continuous stress monitoring and management.

#### Model Robustness

The robustness of the models was tested against various demographic factors and environmental conditions, ensuring their reliability and generalizability across different scenarios and populations.

#### Future Work

Despite the promising results, there are several avenues for future research and improvements in the domain of stress level detection using machine learning:

#### Data Diversity and Volume

Expanding the dataset to include a more diverse population and a larger volume of data can enhance the model's generalizability and robustness. This includes collecting data across different age groups, ethnicities, and cultural backgrounds.



## **Advanced Algorithms**

Exploring advanced machine learning techniques such as deep learning architectures, including Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), could further improve the accuracy and efficiency of stress detection models.

## **Real-World Deployment**

Conducting longitudinal studies and real-world deployments to evaluate the performance and impact of these models in everyday life settings. This will help in understanding the practical challenges and refining the models for better real-world applicability.

## **Integration with Health Systems**

Developing frameworks for integrating stress detection systems with existing health monitoring systems and electronic health records (EHRs) to provide comprehensive health insights and personalized stress management strategies.

## **Interdisciplinary Collaboration**

Promoting interdisciplinary collaboration between machine learning experts, psychologists, and healthcare professionals to develop holistic and user-centered stress management solutions that not only detect but also mitigate stress through personalized interventions.



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