Automatic pain intensity detection by analyzingfacial expressions caused due to pain

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Abstract—One of the most effective, direct, and natural ways for people to express their feelings and intentions is through theirfaces. In this project We put forth a completely automatic facial alerting and recognition system. Yolo method is used for facial expression identification and feature extraction. In this project an alerting system is used to intimate the care takers. Camera monitors the face of the person and capture the images and sendsimages to raspberry pi which processes the images with Yolo algorithm and analyzes the facial expressions then if the pain is detected it immediately intimates to the caretakers with buzzer and mobile application which sends message to the person. This mostly helps to the paralyzed people and elderly people.

***Index Terms*—Yolov4 (You only look once), Raspberry pi, Internet of Things.**

I. Introduction

Pain is an uncomfortable indication that there might bea problem with the nervous system. People typically seekmedical assistance when they experience pain as a primary symptom. Uncontrolled pain not only impairs immune health but also causes discomfort and lowers quality of life. Theability of untreated pain to harm organ systems or the heal-ing process makes pain management essential. Today’s usual work-life balance prevents us from caring for our elderly and disabled patients, making it impossible for them to notify usin case of a medical emergency when they experience acute pain.

Direct conversation with the patient is the most efficient technique to estimate pain severity because it varies greatly depending on the individual. However, there is a group of patients who, when in agony, are unable to speak. Patients whoare crippled, expectant women, and elderly folks fall under thisgroup. We suggest an automatic pain intensity alerting system to aid these individuals. which uses YOLOv4 algorithm for better performance. Using deep neural networks is typical taskinstead we used YOLOv4 for faster results and better accuracy.This paper provides a better solution for alerting the care- takers in case of emergency. We created an alerting systemthat sends immediate notifications through buzzer and mo-bile application. When we are away from home, a mobileapplication is utilized, and a buzzer employed if are far frompatient in our home. The proposed system has the potentialto improve pain management in individuals who are unable toself-report pain, such as those with severe cognitive impair- ment or communication difficulties. Additionally, the systemcould be used to monitor pain in real-time and provide moretimely interventions, leading to improved pain management and quality of life for individuals with chronic pain.

II. Literature

The speech emotion recognition model extracted window- level information using the sliding window technique. The interval-level features, which reflect the difference in contribu-tion from interval-level to window-level, were then calculated based on the extracted window-level features, and finally the window-level and interval-level features were fused for Artificial neural network training.. Then the results were per- formed on emotional database where this model detects only one emotion [1]. An effective facial expression recognition model uses HOG extractor and support vector machine (SVM)classifier for facial expression recognition. The main challengeto expression recognition is variation in light intensity which was reduced by this model through image pre-processing and provides good accuracy. This system has improved insuch a way that a small pose doesn’t affect the histogramof oriented gradients (HOG) features [2]. Facial Expression Recognition model was a new approach compared to earlier

where geometric shape features were used to recognize the facial expression where it includes eyes, nose, lips and cheeks as the features. Graph convolution neural network (GCNN)is used in this model. Length and height of the features are considered as parameters to compare with the original face to recognize the expression of the face. This technique helpedin recognizing the six kinds of expressions. Producing better results was the major goal of this model but not the accuracy [3].

Object (head) identification, segmentation, and attribute estimation using a multitask model (pose estimation). The recommended multitask learning model and attribute estima- tion (position, age) were paralleled to the process of object detection (i.e., the head), which removes the need for manual image cropping or the need for expensive equipment like depth camera sensors. The proposed model showed the good results which can be used in any domain [4]. Automatic subject independent pain intensity estimation model used Res-net neural networks for estimation of pain intensity. On the Heat Pain data set, this model was trained from scratch using several hyper-parameters, a Res-Net 18 model, and a Res-Net 50 model to determine the intensity of the pain. Thedatasets used in this were subjected where it may affect the accuracy but it produced good results on BioVid-HeatPain data set [5]. An investigation into the effectiveness ofa joint deep neural network that is trained and evaluated for four levels of pain categorization has been conducted usinga joint neural network model for pain recognition from faces convolution neural network (CNN) and two Long short-term memory (LSTM) base networks are combined to create the system. In order to detect and identify the level of pain intensity from facial expressions, features taken from CNN arepassed into deep neural network (DNN1) and DNN2, which are three layers. This approach improved recognition ability, particularly for additional categorization and different levels of pain [6]. Object Detection in Complex Scenarios modelhas used Yolov4 algorithm. This model improved the accuracyof identification. This model mainly focused to improve the Yolov4 performance and accuracy. This model improved the recognition of small objects and blurred images. Last but not least, this increased the overall recognition performance to about seventy percent, which improved particularly for small objects and blurry photographs harmed by extreme weather [7]. The study proposed a model based on recurrent neural networks(RNNs) that can continuously estimate pain intensity levels in real-time.The authors described their methodology for collecting data, which involved recording autonomic signals and self-reported pain scores of 33 participants in responseto heat pain stimuli. They then used RNNs to analyze thedata and develop a continuous pain intensity estimation model.The study focused solely on autonomic signals, and it isun- clear whether the proposed model would be effective when combined with other types of physiological or behavioral measures. The study samples in the literature analyzed might not be representative of the general population, as some studiesincluded only patients with chronic pain. This may affect the generalizability of the results to other populations. The accuracy of pain estimation from facial expressions may be affected by individual differences in facial expressions and pain perception, as well as cultural variations [8]. The study proposed a model based on the Supervised Descent Method (SDM) that can accurately detect pain from facial expressions.The authors described their methodology for collecting data, which involved recording facial expressions of 30 participantsin response to heat pain stimuli.They then used SDM to analyze the data and develop a pain detection model. The results of the study show that the SDM-based model achieved high accuracy in detecting pain from facial expressions, witha sensitivity of 96. However, the study was conducted with a relatively small sample size, and further research is neededto determine the generalizability of the findings to larger populations and other types of pain stimuli [9]. The study proposed a curriculum learning approach that trains a deep neural network to recognize pain intensity levels based on facial expressions.The authors described their methodology for collecting data, which involved recording facial expressions of90 participants in response to heat pain stimuli. They then useda curriculum learning approach to train a deep neural network to recognize pain intensity levels. The results of the study show that the curriculum learning approach outperformed several baseline models that used different machine learning algorithms. The authors also found that the model could accurately recognize pain intensity levels across different pain intensities and individuals [10]. **[15]** The authors reviewed various methods used for pain recognition using facial ex- pressions. They found that the most effective methods used deep learning techniques and used large datasets for training. They also identified the need for standardization in datasets and evaluation metrics for pain recognition systems. Authors used artificial neural networks (ANN) for pain recognition. They trained their model on a dataset of facial expressions with and without pain and achieved high accuracy in pain recognition. They found that the most effective methods used deep learning techniques and used large datasets fortraining. They also identified the need for standardization in datasets and evaluation metrics for pain recognition systems.

[16] Personalized automatic estimation of self-reported pain intensity from facial expressions is a promising research area that has the potential to improve pain management and patientcare. Deep learning techniques, such as CNNs and transfer learning, have been found to be effective for developing personalized models for pain intensity estimation.The authors used transfer learning to develop personalized models for pain intensity estimation. The models were trained on a large dataset of facial expressions and self-reported pain intensity scores, and were fine-tuned for each patient to achieve high accuracy in pain intensity estimation. **[17]** They describedthe various methods and techniques used for pain detection from facial expressions, including feature extraction methods, machine learning algorithms, and multimodel approaches.The study provided a detailed overview of the various feature extraction methods used in pain detection, including geometric features, texture features, and appearance-based features. This model have highlighted the importance of developing accurate and reliable pain detection systems that can improve painmanagement and patient care. The use of standardized datasetsand evaluation metrics has been used for the developmentof accurate pain detection system. Deep learning techniques, such as CNNs and RNNs, have been found to be effective for pain detection, and many studies have used these techniquesto develop pain detection systems that achieve high accuracy in pain detection.

III. DESIGN

In the proposed method entire process is done by Raspberry pi. It involves the three major steps in the entire process. Monitoring the footage is done with a USB webcam. Images from the video are extracted every 1-2 seconds and transferredto pi where they are processed and classed. It recognizes the expression of pain while processing the image. If the expression is later determined to be one of pain, informationis then passed to the buzzer, which then makes noise to alert the caretaker. Additionally, output is transferred to a mobile application, which notifies the caretaker with a message. We can watch the patient in picture's face, and if there is a serioussituation, we can contact for assistance right away.

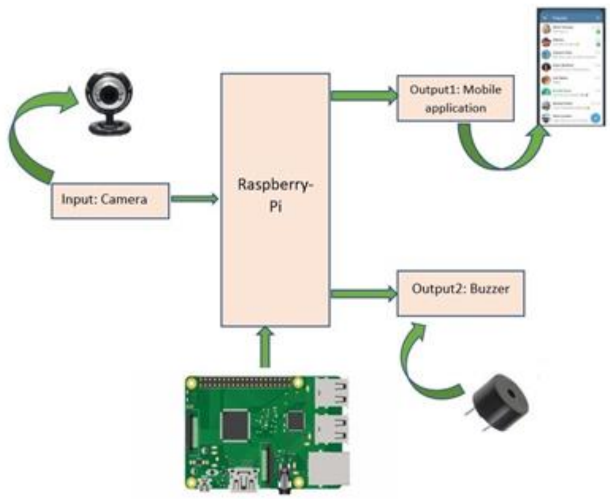

Fig. 1. Block Diagram and all the components used in the hardware realization.

A. Raspberry pi

The Raspberry Pi is a tiny computer that can be used for many different purposes, including military and surveillance applications. The Raspberry Pi 4 model B is the most recent addition to the foundation's lineup. Total number of general-purpose input and output pins on the Raspberry Pi is 40. On the board, there are seven zerovolt pins, two 5V pins, two3V3 pins, and 26 General purpose input output pins (0V). Processor present in Pi 4 Model B uses 20-25 percent less power and performs more than 90 percent efficient than the older version. It includes two tiny 'High-Definition multimedia Interface (HDMI)' ports with a resolution of 4Kp60. Raspberrypi-4 consists of 4-pole stereo and audio port. It consists of SD card slot which is useful for loading operating system, filesand images needed in it. It has 'Universal serial Bus (USB)'-Cconnector. Since pi-4 has 64-bit architecture Operating shouldalso be of 64 bit which was released by the foundation in recent times. The PI-4 B's 'Graphics processing unit GPU (GPU)' supports Blue Ray video playback and 3.0 graphics.It features four 'USB' 3.0 and 2.0 connectors. They can be connected to external devices such as mouse, keyboards, and other peripherals. True Gigabit Ethernet is included into the Pi-4-B, allowing it to send Ethernet frames at a rate of 1billion bits per second. Raspbian OS can play a crucial rolein providing a reliable and efficient platform for collectingand processing physiological data. We can implement machine learning algorithms for analyzing the collected data and detect- ing patterns associated with pain. Raspbian OS provides sev- eral pre-installed machine learning libraries and frameworks, such as TensorFlow, Scikit-learn, and Keras, which can be used for developing and implementing these algorithms. Moreover, Raspbian OS can also facilitate the communication and sharingof data between the automatic pain intensity detection system and other devices or systems, such as cloud-based data storageand visualization tools. This can help healthcare providers to access and analyze the pain data in real-time, enabling them toprovide timely interventions and pain management strategies.

B. Camera

The purpose of a webcam is to record or send video toa computer or computer network. They are mostly used for social networking, livestreaming, and security. Webcams are commonly connected to a device using USB. Software exists that enables PC-connected cameras to detect movement and listen for sound, recording both when they are detected. The charge-coupled device (CCD) response of a webcam is linearlyproportional to the amount of incoming light. Cameras' useof CCD enables them to record visual information as an image or video. The size of a webcam's colour pixel maylie in the range of 5 to 10 µm. Additionally, larger, movable lenses found in USB webcams produce higher overall image quality. With an adjustable lens, you can fine-tune the focus settings and change the focal length for close-up or far-away shots to ensure that the topic you are capturing is always in focus. webcam's field of view (FOV) is 60- degrees which can capture one person sitting in front of a computer. This webcam captures a horizontal 16:9 landscape frame. This has the feature of autofocus and lowlight correction. The image and video quality of a USB web camera are determined by several factors, including the resolution, frame rate, and sensorsize. Most USB web cameras support HD resolution (720por 1080p) and a frame rate of 30 frames per second (fps). Some high-end models can capture 4K video at 60 fps. USB web cameras are compatible with most operating systems, including Windows, macOS, and Linux. They also work with most video conferencing software, such as Zoom, Skype, and

Microsoft Teams. : The field of view of a USB camera isthe area of the image it captures. It is typically measuredin degrees, and a wider field of view means more of thesurrounding area is visible in the image.

C. Buzzer

Many industries employ piezo element buzzers, including telecommunications, home appliances, cars, alarm systems, etc. A Piezo electric buzzer is such that which uses piezo electric effect to produce a tone. The initial motion of buzzeris created by applying a voltage to piezo electric material, which is converted to sound. The operating voltage range of a piezo electric buzzer can vary, but is typically between 3V and 24V. The resonant frequency of the piezoelectric crystal is the frequency at which it vibrates most efficiently, and this is typically in the range of 1kHz to 4kHz for most buzzers. The SPL is a measure of the loudness of the sound produced bythe buzzer, and it is typically measured in decibels (dB). The SPL of a piezo electric buzzer can range from 70dB to 110dB or higher, depending on the design. The current consumption of a piezo electric buzzer can vary depending on the operating voltage and the load it is driving, but is typically in the range of 1mA to 20mA. The operating temperature range of a piezo electric buzzer can vary, but is typically between - 20°C to +70°C. Piezo electric buzzers can be mounted using a variety of methods, including through-hole, surface-mount, or panel-mount. The frequency range of a piezo electric buzzer determines the pitch of the sound it produces. Most piezo electric buzzers have a frequency range of 2 kHz to 4 kHz.The operating voltage of a piezo electric buzzer is the voltage required to generate sound. Most piezo electric buzzers require a voltage between 3V and 12V. Piezo electric buzzers are known for their low power consumption, making them ideal for battery-powered devices.

IV. IMPLEMENTATION

The above picture displays the project's execution sequence in different levels. Object detection algorithms are widely usedin many areas of research and industry, including the field of pain expression detection. The YOLO (You Only Look Once) algorithm is a popular object detection algorithm that has been used to identify pain expressions in images and videos. Hereis an overview of how the YOLO algorithm works for pain detection. The pain detection system is implemented using Python and TensorFlow libraries. The dataset used for trainingand testing the model consists of facial images of patients in pain and without pain. The images are collected from various sources, including publicly available datasets. The images are pre-processed by resizing them to a fixed size and normalizingthe pixel values. Camera continuously monitors the face of a person. As a part of the video processing images are taken then the images are processed in the pi. Initially bounding boxes will be generated around the object. More than onebox will be generated around one object. Whenever, the boxesare generated confidence score also will be generated on the top of the box which is also known as probability. So, the box with highest score will be considered and all other boxes will be suppressed with command "NMS" (non-maximum suppression). Then it identifies whether the object in the box is a person's face or any other object. In case, if the object in the box is not a person's face, then it will discard the image without further processing. If in case it contains a person's face then it starts further processing of the image. At first it converts the image into grey scale image then it compares the extracted features with trained images. It compares the eyebrows, pupil size, cheeks and lips these are the features which are compared. After that if it classifies it as pain then Pi sends immediately the output to buzzer where it emits noise and an alert message to mobile application.

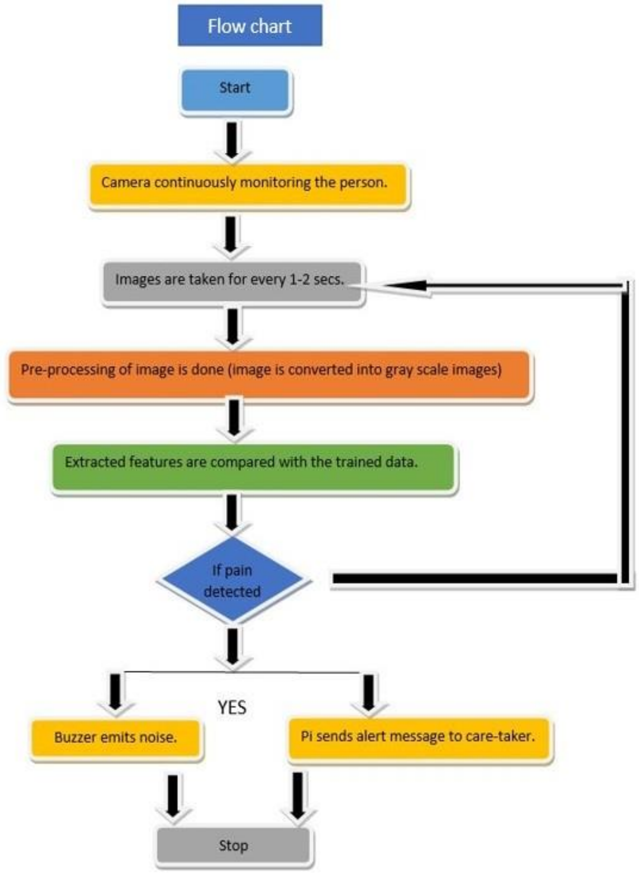

Fig. 2. Flow chart of proposed system.

V. Results and Discussion

A. Discussion

Assistance of pain is the major goal of this initiative. For this application, processing of the images is much faster than previous designs. This is the result of the YOLOv4 algorithm

Fig. 3. Result of proposed system

which provides the best accuracy. The comparision for the previous designs and proposed design is as follows.

Previous designs: In earlier designs/systems many algorithmswere used to analyze the facial expressions like "happy"," Sad"," anger", "surprise". Further many systems were also introduced using different neural networks. After some time, pain intensity was also detected using technologies like sliding window, RCNN, Fast RCNN, Faster RCNN where images should be trained which includes a complex work and the accuracy will also not be up to the mark. And training thousands of images is also a complex work and risky process. And also, previously there was no alerting system on whichit notifies at much faster to the care takers.

Proposed design: The proposed design of this project reducesthe complexity of the work of training the images or getting data sets from the internet. YOLOv4 algorithm is faster than the

Neural networks used in the previous designs such as RCNN, Fast RCNN, Faster RCNN etc.. . . This algorithm provides better accuracy rate than the other designs. In this design, Identification and classification is much faster as compared to previous designs. Yolov4 has not yet been used for this application by anyone. This project gives the better alerting system which saves the lives of people in case of emergency. This alerting system such type which alerts us irrespective of the distance we are with the patient. Advantages of the proposed design are: Power consumption is less, less manual work, Less complexity in circuit, more efficient and better accuracy

VI. Conclusion and Futurescope

A patient's health status can be determined by their levelof pain, which is a common medical symptom. Self-reported methods of evaluating one's own level of pain are well- established, while automatic pain detection technologies that analyze facial expressions are rapidly developing. These tech- niques hold the promise of more effective, comfortable, and affordable treat of pain. In this paper, a deep learning model based on Yolo algorithm is proposed where it assists certain category of people who are suffering with pain when they can-not inform to the care-takers. Whenever the pain is detected, itimmediately alerts the care-taker with alert message as-well-asbuzzer emits sound. This model helps though the care-takeris far away from the patient. As this model is based on Yolo algorithm this is more accurate and efficient than the previous designs. In conclusion, the use of the YOLOv4 algorithm for automatic pain intensity detection has several potential advantages, including real-time detection, high accuracy, com-putational efficiency, flexibility, and objective measurement. However, there are also several challenges that need to be considered, such as the need for a large and diverse dataset, potential biases, and ethical considerations related to privacy and autonomy.

To further develop this model, one has to work on one ofthe following suggestions.

1. We used image capturing with one camera where it workswhen the patient is on one side but to extend this one can work with four cameras where we can monitor the person from all sides which will be more effective.
2. Current pain detection systems primarilyrely on facial expressions to detect pain. However, there is growing interest indeveloping multi-modal systems that can detect pain using other physiologicalsignals, such as heart rate, skin conduc- tance, and brain activity. Multi-modalsystems may providemore accurate and reliable pain detection, particularly in caseswhere facial expressions are not visible or reliable.
3. Pain is a highly subjective experience, and individuals may have different pain thresholds and expressions. Person- alized pain detection systems could be developed that takeinto account individual differences in pain expression andperception. These systems could be trained on individual data to provide personalized pain detection and management recommendations.
4. Pain detection systems could be integrated with pain management systems to provide a comprehensive approachto pain assessment and treatment. For example, pain detection systems could provide real-time feedback to pain managementsystems, allowing for more personalized and effective pain management.

The future scope for pain detection systems is wide and varied, with potential advancements in multi-modal pain de- tection,personalized pain detection, and integration with pain management systems. As technology continues to advance, pain detection systems will continue to play an important role in improving pain assessment and management.

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