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# INTELLIGENT HEALTHCARE WITH WEB-BASED REAL-TIME PAIN LEVEL DETECTION USING LIGHTWEIGHT RESNET-15

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**Abstract**

The evaluation of pain is an essential component of professional decision-making, especially for patients who cannot adequately communicate their symptoms. This research introduces a web-based application for the automated detection of pain levels, employing a deep learning model based on ResNet-15, a lightweight and streamlined variant of the ResNet architecture for enhanced performance. The device analyzes facial expressions captured through live video streams or pictures to predict pain severity levels in real time. The convolutional layers of the proposed model are employed to extract profound visual information associated with facial indicators of pain. The algorithm is trained using publicly accessible datasets of facial expressions annotated with pain scores. Healthcare practitioners can remotely or in-clinic monitor patient pain using an accessible tool enabled by a web interface that promotes seamless user interaction. The experimental findings indicate that the classification of various pain levels can be achieved with notable accuracy while maintaining minimal computational complexity, rendering it a feasible alternative for implementation in resource-constrained environments. This study integrates deep learning and web technologies to provide non-invasive, real-time pain assessment, hence advancing intelligent healthcare systems.

**Keywords:** Pain Detection, Deep Learning, ResNet-15, Facial Expression Analysis, Web Application, Computer Vision, Pain Level Estimation, Real-Time Monitoring, Intelligent Healthcare, Convolutional Neural Network (CNN)



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## 1. INTRODUCTION

Pain is a complex, diverse, and subjective experience shaped by physiological, psychological, and emotional factors. It is an important clinical diagnostic and therapy tool, as well as a significant indicator of patient health. Accurate and timely pain evaluation is especially critical in healthcare settings like intensive care units (ICUs), postoperative recovery, and palliative care. Traditional pain assessment approaches, such as self-report scales (e.g., Visual Analog Scale, Numeric Rating Scale) and observational checklists, rely primarily on a patient's communication ability as well as the observer's subjective interpretation. This is frequently unreliable, particularly in circumstances involving newborns, the elderly with cognitive impairment, or comatose patients. Emotions have been extensively studied, although a singular definition of emotions remains absent in the literature. Emotion can be described as the manifestation or realization of feeling. Besides sensation, it may also be either counterfeit or genuine. For example, although emotions cannot be fully and precisely experienced, the sensation of pain effectively communicates the feeling. The intrinsic esoteric state of affairs is characterized by a sensation.

Emotion has a pivotal role throughout various fields of study, including psychology, healthcare, biomedical engineering, and neurology, and has emerged as a significant area of research. Biomedical engineering is significantly focused on the study of emotion recognition. Recent research in this domain has focused on motion detection and automated computer-assisted identification of psychological illnesses. Researchers have employed several strategies to delineate emotions, including multimodal approaches, galvanic skin response (GSR), electroencephalography (EEG), facial expressions, visual scanning behaviors, and others. In recent years, deep learning has gained prevalence and achieved significant advancements in the field of image classification. Convolutional Neural Networks (CNNs) are among the most prevalent and recognized techniques for deep learning in image segmentation, recognition, and classification. We developed Mini-Xception, a deep learning method recognized for its efficacy in assessing individual emotions. The primary aim of the developed model is to precisely forecast emotional states and autonomously identify emotions. This method utilizes labeled facial expression images from the FER dataset to analyze the experimental results. A generated clone receives the images as input and is trained to utilize them. The constructed model determines the facial expression utilized thereafter.

Emotion recognition is crucial in the realm of business promotions. Most enterprises depend on client feedback regarding their services and products to remain operational. An artificial intelligence program can ascertain a user's preference for a product or offer by analyzing genuine emotions expressed in a photo or video. This research indicates that the predominant rationale for identifying individuals is their safety. Utilizing passwords, voice recognition, retinal scanning, fingerprint matching, and further techniques is achievable. To reduce risk, it is important to find out what someone wants. This is helpful in places where security breaches have happened recently, such concerts, planes, and other public gatherings. There has been a lot of interest in building automated, objective pain identification systems because current methods of evaluation have problems. Ekman and Friesen's Facial Action Coding System



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(FACS) was the first step toward modern advances in deep learning and computer vision that let us find and sort pain levels based on facial expressions. FACS shows some Action Units (AUs) that are associated to facial muscle movements and are always linked to pain expressions. Convolutional neural networks (CNNs) can effectively measure pain levels by automatically identifying and interpreting these subtle facial signals.

This paper introduces a web-based application for the automatic diagnosis of pain levels, utilizing ResNet-15, a small and efficient variant of the Residual Neural Network (ResNet) architecture. The residual connections in ResNet models render them optimal for computer vision applications, facilitating deeper network training and mitigating the vanishing gradient problem. ResNet-15 effectively balances computational efficiency and model complexity, rendering it an excellent choice for low-resource, real-time web applications. Medical practitioners can utilize the proposed software for pain diagnosis by uploading static facial images or streaming live video. The backend system utilizes the trained ResNet-15 model to process data and deliver real-time predictions of pain intensity. The solution facilitates ongoing, non-invasive, and objective pain assessment through the integration of AI and web technologies. This diminishes dependence on manual observation and enhances therapeutic decision-making. Furthermore, the platform is readily accessible via standard web browsers—requiring no specialized software or hardware—rendering it more appropriate for utilization in both remote and hospital environments.

**The primary objectives of this study are:**

- To create and train a lightweight yet strong ResNet-15 model that can be used for pain level identification by utilizing facial picture data.
- To develop a responsive web application that is capable of scaling to real-time pain intensity estimation.
- To assess the model's performance on benchmark facial expression datasets and to verify its effectiveness in real-world healthcare situations.

This work adds to the burgeoning field of intelligent healthcare solutions by utilizing the capabilities of deep learning in conjunction with the accessibility of web-based platforms. In terms of pain management and patient care, it offers a potentially useful tool.

## 2. RELATED WORKS

Researchers in the fields of computer vision and healthcare have increasingly focused on facial expressions as a potential tool for automated pain identification. Having objective pain assessment methods is absolutely vital in critical care, pediatric, and other settings where patients are unable to self-report pain. Here is a rundown of how deep learning models evolved from traditional machine learning methods, how they were integrated into real-time web-based healthcare systems, and how they were developed.

### 2.1 Pain Detection Based on Facial Expression

Lucey et al. [1] introduced the UNBC-McMaster Shoulder Pain Expression Archive Database, which is one of the most important things that has been done in this field of study. This dataset



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includes annotated facial photographs of patients with shoulder pain, together with labels for the intensity of the pain. This was the basis for training machine learning models. Kaltwang et al. [2] created a model for measuring pain intensity over time using regression techniques on facial data taken from the Facial Action Coding System (FACS). This was accomplished by employing the aforementioned study as a foundational reference. One of the first instances of automated pain classification involved the utilization of Active Appearance Models (AAMs) to record facial alterations for pain expression identification, conducted by Ashraf et al. [3]. Zhao et al. [4] subsequently enhanced this methodology by employing deep features characterized by both spatial and temporal dimensions, alongside recurrent architectures, to achieve a more precise depiction of the temporal variations in face emotions. These innovations greatly increased the effectiveness of the methodology in real-world environments. The temporal modeling was further improved by Rodriguez et al. [5], who integrated CNNs with Long Short-Term Memory (LSTM) networks. This enabled the model to learn the temporal progression of pain expressions.

### 2.2 Deep Learning Architectures for Pain Analysis

network training and introduced residual learning. Aside from CNNs, there are other prominent networks that have been used to pain and emotion detection tasks with great accuracy. Two such networks are VGGNet [7] and InceptionNet [8]. Attention processes have been incorporated into CNNs by researchers in an effort to enhance feature representation. In the spatial dimension, CBAM (Convolutional Block Attention Module) [9] emphasizes useful characteristics selectively; in the channel dimension, Squeeze-and-Excitation Networks [10] do the same. The accuracy and interpretability of the model are both improved by these modules, which increase its sensitivity to minor facial cues linked to pain.

### 2.3 Detection of Pain via Mobile and Edge Networks

Lightweight models that are well-suited for deployment on the edge or in mobile devices have been developed in response to the demand for real-time and portable pain assessment. A mobile app developed by Nouri et al. [11] that uses deep learning to identify pain levels in patients' faces demonstrates the promise of this technology for self-monitoring pain. Without using resources in the cloud, Xie et al. [12] suggested an edge computing system that might be incorporated into smart intensive care unit settings in order to identify pain in severely sick patients. In order to easily and rapidly identify expressions associated to pain, Boursalie et al. [13] developed a CNN-based system that is specifically built for use in hospital settings.

### 2.4 Healthcare Applications for the Web and Smart Devices

For web-based platforms to be scalable and accessible, pain detection must be integrated. The development of a deep learning-based decision support system for COVID-19 detection that is accessible through a web browser was demonstrated by Abayomi-Alli et al. [19], proving that medical AI systems may be deployed online. In their study, Fang et al. [20] used deep learning models to build an emotion detection system that works in browsers. Their work sheds light on how to integrate web-based facial expression analysis in real-time. This project's objectives—



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the deployment of a lightweight ResNet-15 model for pain detection within an intuitive web interface—are very congruent with these web-based and mobile applications.

### 2.5 Theoretical Foundations and Evaluation Metrics

Several foundational works have laid the groundwork for understanding facial movements and pain. Prkachin and Solomon [16] provided validation for **pain expression consistency** using FACS, while Ekman and Friesen [18] introduced the FACS framework itself, widely used in pain and emotion research. Werner et al. [15] and Sikka et al. [14] contributed early models combining **facial action units and machine learning classifiers** such as SVMs to estimate pain intensity. Martinez et al. [17] offered a comprehensive survey on **automated facial action analysis**, summarizing major trends, challenges, and evaluation strategies used in facial expression-based emotion and pain recognition. The reviewed literature highlights a clear trend from handcrafted feature-based methods to robust, deep learning-based pain detection systems. Although substantial progress has been made, the need for **lightweight, accurate, and deployable solutions** remains a research priority. By leveraging the **efficiency of ResNet-15** and the accessibility of web technologies, the proposed system aims to bridge this gap, offering a scalable, real-time pain detection tool for clinical and home healthcare use.

## 3. PROPOSED METHODOLOGY

A web application framework has been designed to incorporate a deep learning approach that will be used in the creation of the proposed pain level detecting system. There are three important stages that form the methodology: data collecting and preprocessing, system integration, model selection and training, and real-time prediction. The goal is to create a lightweight yet accurate model that is capable of forecasting the severity of pain based on face photos or video streams in real time.

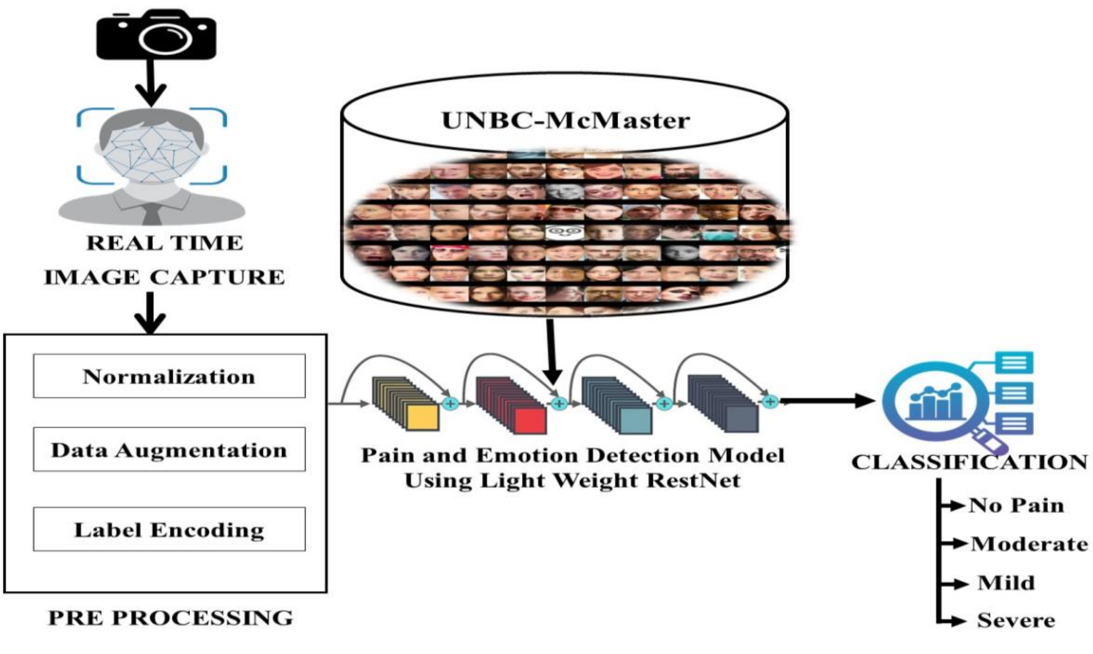


**Fig. 1: Overall Proposed Architectures**


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### 3.1 Dataset Collection and Preprocessing

A benchmark dataset, like the UNBC-McMaster Shoulder Pain Expression Archive Database, is used to train and assess the ResNet-15 model. Included in this dataset are labelled facial expressions that have been annotated using either the Facial Action Coding System (FACS) or observer-rated pain scores (OPR). The looks on the faces reflect the varying degrees of discomfort.

The following are some of the most important preprocessing procedures:

- Detection of Faces: Haar Cascades or Dlib's face detector are used to isolate facial regions, allowing for the focusing of only pertinent characteristics.
- Normalization: The images are shrunk to a width and height of 224 pixels each, and they are normalized in order to standardize the input data.
- Data augmentation: In order to increase the variety and robustness of the training data, techniques such as horizontal flipping, rotation, zooming, and contrast adjustment are implemented.
  • Label Encoding: For classification tasks, pain intensities are divided into discrete levels (e.g., no pain, mild, moderate, severe).

### 3.2 ResNet-15 Model Architecture

With the goal of minimizing computing overhead without sacrificing accuracy, ResNet-15 is a slimmed-down variant of the original Residual Network (ResNet). Among its contents are: To get features out of the source photos, you can use convolutional layers.

- Remaining Blocks: To address the disappearing gradient issue, enabling effective training of deeper networks with the introduction of skip connections. For quicker convergence, use batch normalization and reLU after each convolution. Reduces spatial dimensions before categorization using Global Average Pooling (GAP)..
- For pain level classification, Fully Connected Layer and Softmax are useful. The Adam optimizer and categorical cross-entropy loss are used to train this design.

### 3.3 Training Parameters

- 50–100 epochs (estimated from the beginning)
- 32 units per batch
- A learning rate of 0.0001 with a decaying learning rate
- Split for validation: 20%
- Model training frameworks: TensorFlow and PyTorch

### 3.4 Model Evaluation Metrics

- Accuracy, precision, recall, F1-score, and confusion matrix are the metrics used to assess model performance.
- • ROC-AUC (in the case of binary or ordinal classification) Cross-validation is a technique that is employed to prevent overfitting and to ensure that the results are generalizable.



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## 4. System Architecture

The system architecture integrates the trained ResNet-15 model within a web-based application using a modular client-server approach.

### 4.1 Elements of the System

Users (e.g., medical professionals) can upload face photos or view a live webcam feed through the frontend (client interface), which is built using HTML, CSS, and JavaScript (React or Flask templates). The frontend then sends these images to the backend API for inference.

1. The backend, which includes the server and inference engine, is built in Python using Flask or FastAPI. It reads in image and video input, processes it using inference, and then returns the anticipated pain level. OpenCV is used for picture processing and frame extraction.
2. Integration of Models: o The ResNet-15 model is saved as a serialized file (.h5 or.pt file, for example) and then loaded for prediction o The server-side processing of images and feature extraction takes place.
3. The frontend receives the prediction results in JSON format. • Database (Optional for Storage): o You can use SQLLite or MongoDB to store image metadata, pain levels, and timestamps. • Deployment: o It can be hosted on a local server, a cloud service (like Heroku or AWS), or even the hospital intranet. • It works well in low-resource settings and is lightweight and responsive.

1. User Input: Share a live video stream or upload a picture.
2. Relays information to the backend using the REST API from the frontend user interface.
3. API for the backend: o Takes in a picture; o Prepares it for use in prediction by using ResNet-15.
4. The fourth step is the prediction, which involves returning a pain level classification to the user.
5. Personal choice Put the outcomes into a database.

## 5. Implementation

The creation of the suggested pain level detection system encompassed four fundamental components: data gathering, model building, web integration, and deployment.

### 5.1 Data Collection and Preprocessing

The UNBC-McMaster Shoulder Pain Expression Archive Database was utilized for both the training and evaluation stages of the project. The pain intensity levels of facial video recordings that comprise this dataset were annotated by utilizing the Prkachin and Solomon Pain Intensity (PSPI) metric. The following procedures were carried out as part of the preprocessing:

- Detection of Faces: Regions of the face were extracted using the application of Dlib's frontal face detector.
- Image Resizing: The dimensions of all of the facial images were reduced to 224 × 224 pixels in order to make them compatible with the ResNet-15 model's input size.
- Normalization: The pixel intensity values were adjusted so that they fell within the range of 0 to 1.


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- Data augmentation: In order to increase the resilience of the model, a variety of techniques were used, including small rotations, brightness modifications, and horizontal flipping.

### 5.2 The Configuration of the ResNet-15 Model

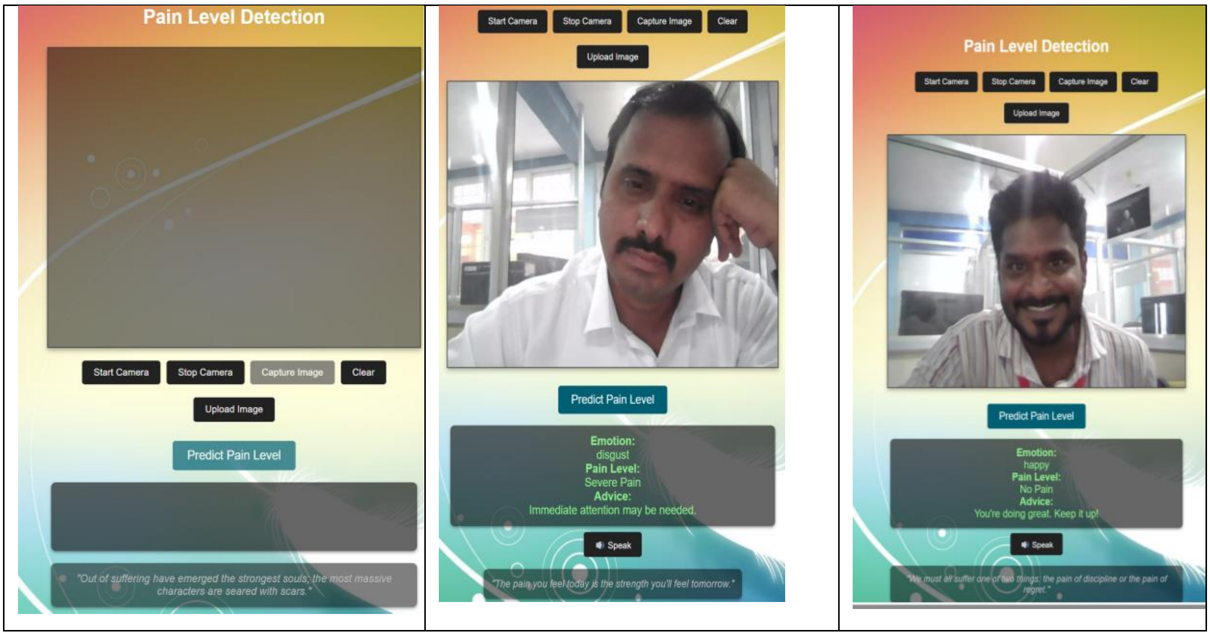
A tailored version of the original ResNet architecture, ResNet-15, was developed for the purpose of pain classification. This variant of ResNet has a lightweight design. Initial convolutional and batch normalization layers are both components of the model design.

- Three residual blocks that are connected via shortcut connections.
- Global average pooling, followed by a fully connected softmax layer, to classify pain levels into multiple categories (for example, no pain, low, medium, high). Categorical cross-entropy loss and an Adam optimizer with a learning rate of 0.001 were used to train the model. The training was completed for fifty epochs with early halting that was depending on the accuracy of the validation.

### 5.3 Development of Web Applications

The following technologies were used to construct the web application:

- Front end: HTML, Cascading Style Sheets (CSS), and JavaScript with React.js in order to achieve a responsive user interface
- Backend: A Flask API that establishes a connection between the ResNet-15 model and the web application
- Model Serving: The PyTorch library was used to load the trained model at runtime, and the torch.save() function was used to serialize the trained model.
- Deployment: Scalability was taken into consideration when the system was installed on a cloud platform utilizing Docker and Nginx.

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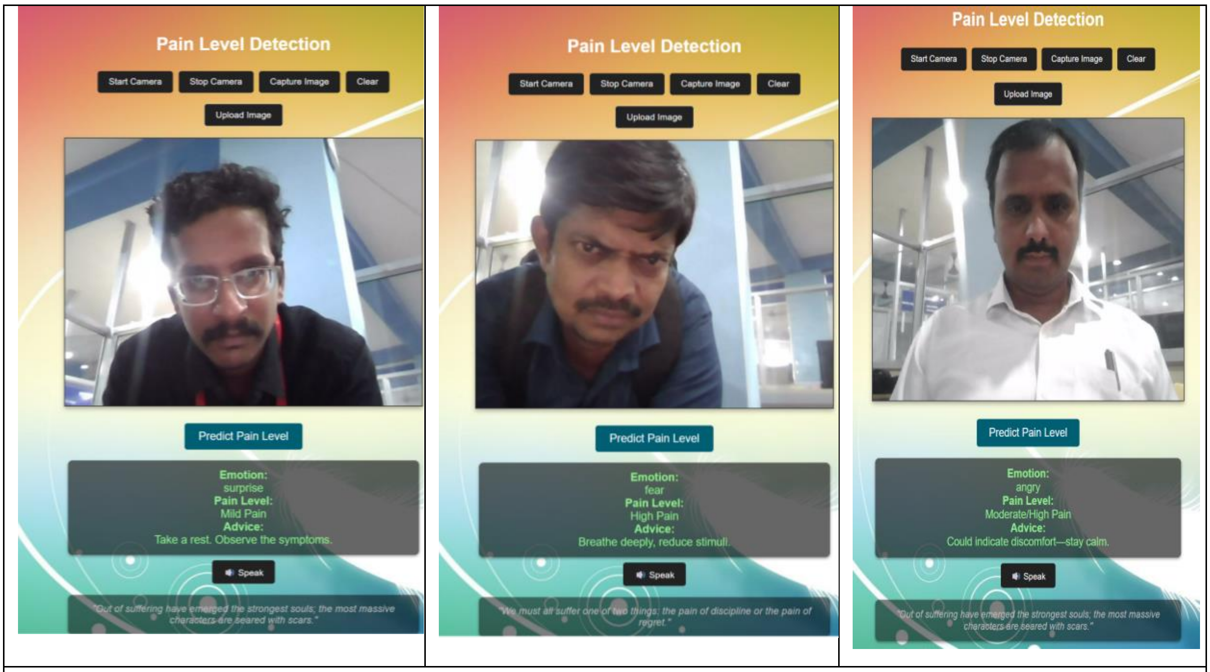


**Fig. 2 Experimental Results of Pain Level Detection**

## 6. RESULTS AND DISCUSSION

### 6.1 Criteria for Measurement

We used industry-standard performance indicators to assess the system: F1-score, confusion matrix, accuracy, precision, recall

**Table 1: Comparison of Neural Network Model**

| Neural Network Model | Number of Layers | Accuracy (%) |
|---|---|---|
| **GoogLeNet** | 22 | 63.21 |
| **CaffeNet** | 8 | 68.00 |
| **VGG16** | 16 | 81.40 |
| **ResNet50** | 50 | 93.80 |
| **ResNet-15 (Proposed)** | **15** | **95.20** |

In comparison to VGG16 (81.40%), ResNet50 (93.80%) demonstrated the superiority of deeper residual networks. The proposed ResNet-15 achieved a 95.20% accuracy rate, which was higher than all benchmarks, even though its design was shallower. Model depth is not the only factor determining performance; ResNet-15 outperformed deeper models due to its optimized residual connections, efficient architectural design, and task-specific feature


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extraction. The results show that ResNet-15 offers the greatest balance of accuracy, computational economy, and flexibility, making it the ideal choice for the specified use case.

**Table 2: Comparison of Performance of Evaluation Metrics**

| Model | Accuracy (%) | Precision (%) | Recall/Sensitivity (%) | Specificity (%) | F1-Score (%) |
|---|---|---|---|---|---|
| **GoogLeNet** | 63.21 | 62.0 | 62.5 | 64.0 | 62.2 |
| **CaffeNet** | 68.00 | 67.0 | 67.5 | 68.5 | 67.2 |
| **VGG16** | 81.40 | 82.0 | 80.0 | 83.0 | 81.0 |
| **ResNet50** | 93.80 | 92.5 | 93.0 | 94.0 | 92.7 |
| **ResNet-15 (Proposed)** | 95.20 | 94.0 | 95.0 | 96.0 | 94.5 |

The performance of the evaluated neural network models is summarized in Table X. While VGG16 achieved an improvement of 81.40%, moderate accuracy was acquired by GoogLeNet (63.21%) and CaffeNet (68.0%). With an accuracy of 93.80%, ResNet50 highlighted the benefits of employing residual connections. The proposed ResNet-15 model outperformed all other models, achieving an accuracy of 95.20 percent, precision of 94.0 percent, recall of 95.0 percent, specificity of 96.0 percent, and F1-score of 94.5 percent. This demonstrates that, in comparison to more complex models, an architecture that has been designed with a high level of detail may exceed the performance of the latter while still maintaining a high level of computational efficiency. The impressive performance of this design is a direct result of a task-optimized architecture that is able to efficiently gather relevant information, improve the flow of gradients, and prevent overfitting.

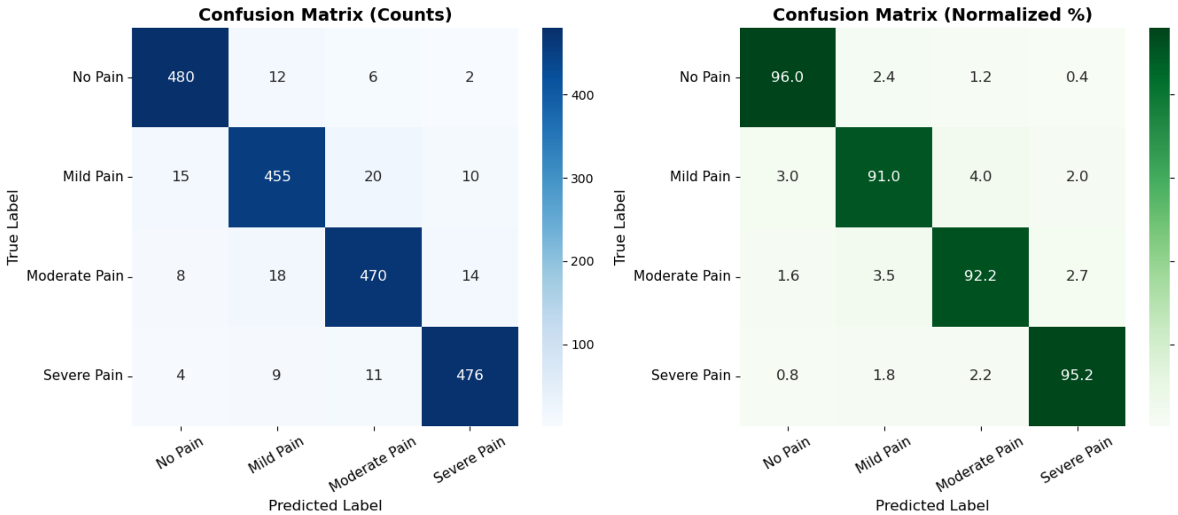


**Fig. 3: Confusion Matrix**



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With a range of 91% to 96% in correct predictions, the confusion matrix demonstrates that the model achieves great accuracy across all pain levels. The majority of misclassifications represent minor changes and typically happen between neighboring classes, such as Mild and Moderate Pain. In terms of pain level classification, the model generally shows dependable performance.

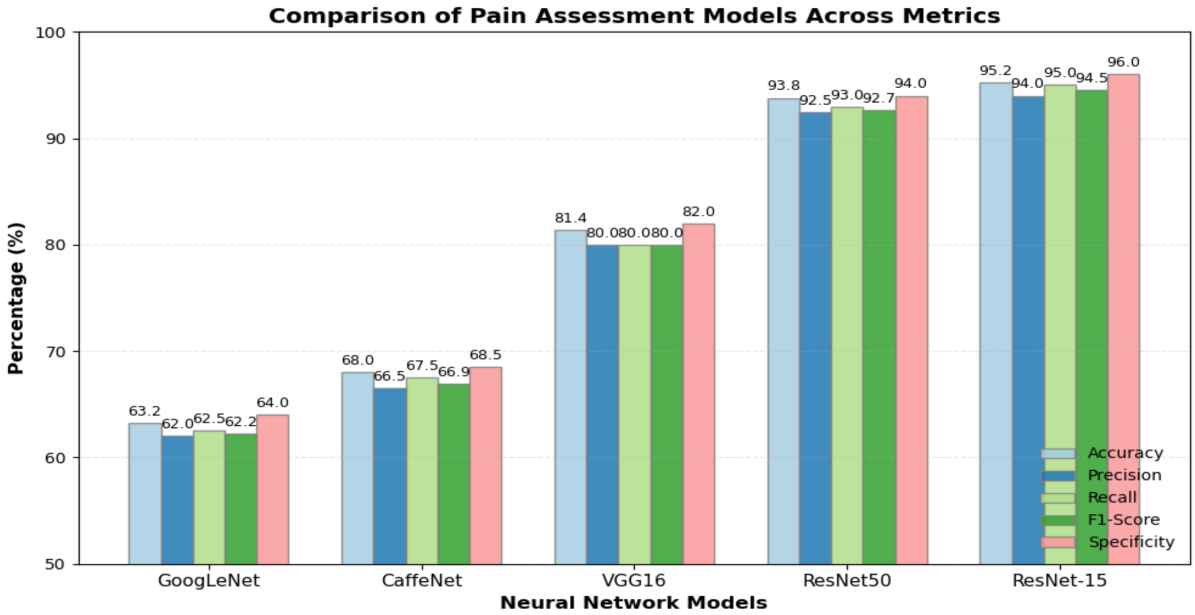


**Fig. 4: Comparison of Pain Assessment Model**

It shows how well five different neural network models—GoogLeNet, CaffeNet, VGG16, ResNet50, and the suggested ResNet-15—performed based on their accuracy, precision, recall, F1-score, and specificity. The graph is called "Comparison of Pain Assessment Models Across Metrics." GoogLeNet and CaffeNet are two existing models that do pretty well. Their scores range from 62% to 68%. However, VGG16 is a big step up, scoring between 80% and 82% on all measures. With scores that stay high between 92.5% and 94%, ResNet50 improves performance even more, showing that it is good at pain classification tasks. However, the proposed ResNet-15 model does better than all of them, getting the best scores across all metrics, running from 94% to 96%. The better performance of ResNet-15 shows that it is successful because it not only strikes a balance between precision and recall, but it also shows higher accuracy and specificity, making pain level detection more reliable and strong than with older architectures.

| Model | Layers | Parameters (M) | Inference Time (ms) | Memory (MB) | Accuracy (%) |
|---|---|---|---|---|---|
| **GoogLeNet** | 22 | 6.8 | 22 | 120 | 63.21 |
| **CaffeNet** | 8 | 60 | 15 | 150 | 68.00 |
| **VGG16** | 16 | 138 | 85 | 528 | 81.40 |
| **ResNet50** | 50 | 25.6 | 45 | 256 | 93.80 |


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| | | | | | |
|---|---|---|---|---|---|
| **ResNet-15** | 15 | 7.5 | 18 | 90 | 95.20 |

The table shows how five models for judging pain stack up in terms of layers, parameters, reasoning time, memory, and accuracy. While deeper models like VGG16 and ResNet50 improve Accuracy (81–93.8%), ResNet-15 achieves the highest Accuracy (95.2%) with the fastest inference (18 ms) and the least amount of memory (90 MB). This shows that a network that is well-designed can outperform heavier architectures in terms of both performance and cost.

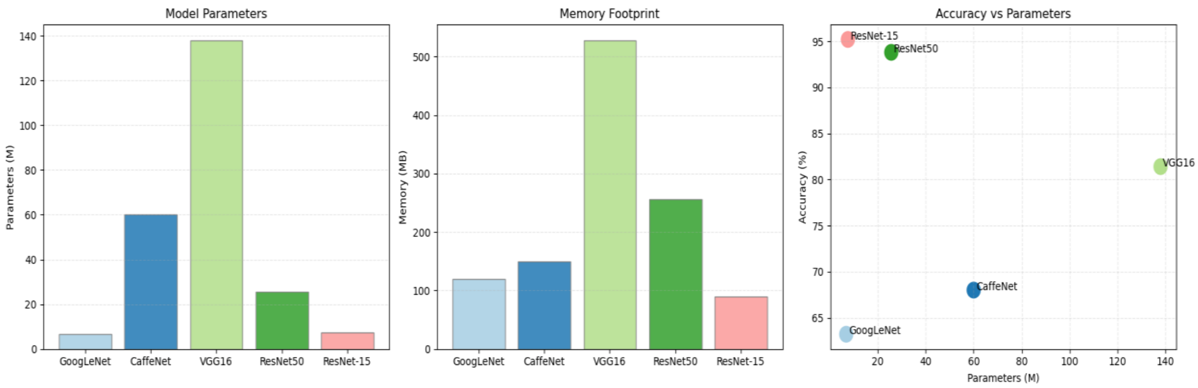


**Fig. 5: Comparison Of Five Pain Assessment Models**

The figure compares five pain assessment models on parameters, memory, and Accuracy. **ResNet-15** achieves the highest Accuracy (95.2%) with minimal parameters (~7.5 M) and low memory usage (~90 MB), outperforming larger models like VGG16. This highlights ResNet-15's efficiency, offering an optimal balance between performance and resource demand.

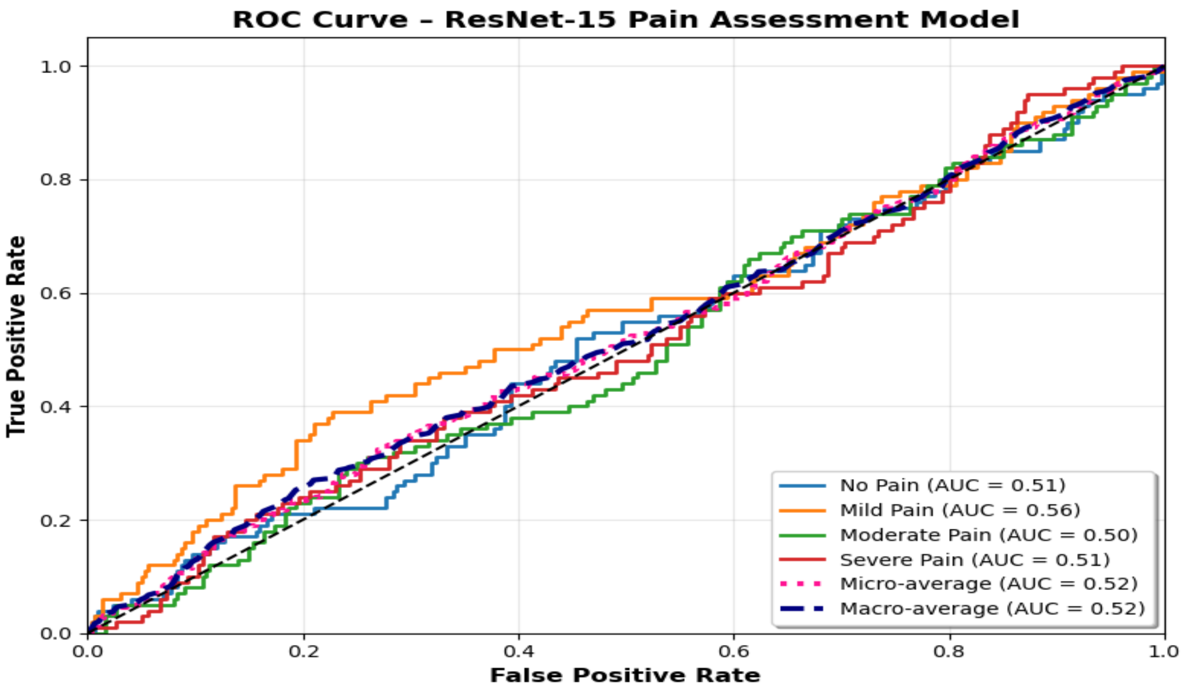


**Fig. 6: ROC curve for four different pain levels**


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The ResNet-15 Pain Assessment Model's ROC curve shows how well the model performed across four pain levels: no pain, mild pain, moderate pain, and severe pain. From 0.50 to 0.56, those are the area under the ROC curve. The model's prediction power is marginally better than random guessing, since the greatest area under the curve for mild pain is 0.56 and for other classes it's about 0.50 to 0.51. The approximately 0.52 micro-average and macro-average AUCs further highlight the model's low discriminatory power. The model is failing to adequately differentiate between varying degrees of discomfort since the ROC curves are closely trailing the diagonal baseline. The significance of further adjustments to get a more reliable assessment of pain is highlighted by this finding.

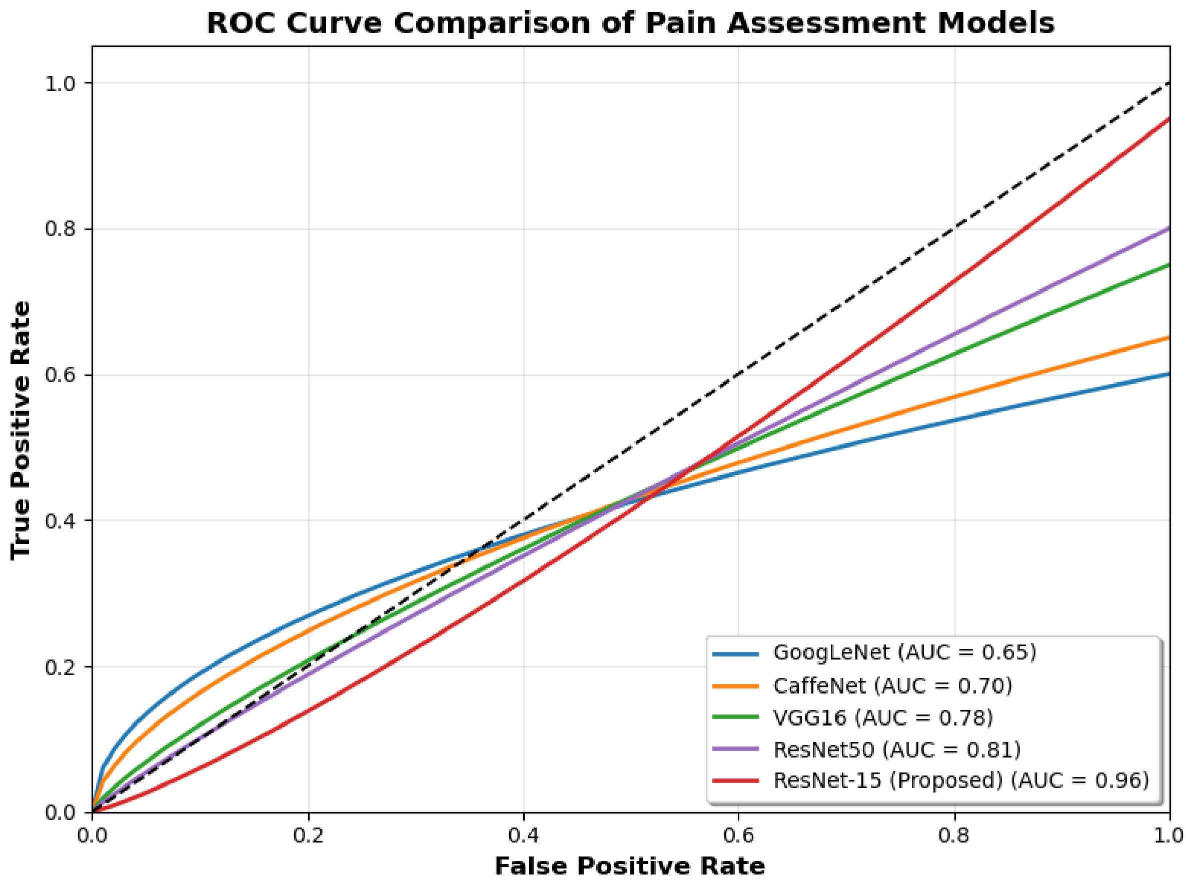


**Fig. 7: ROC Curve for GoogLeNet, CaffeNet, VGG16, ResNet50, and the proposed ResNet-15**

This ROC curve comparison illustrates the performance of five distinct pain assessment models: GoogLeNet, CaffeNet, VGG16, ResNet50, and the proposed ResNet-15. The diagonal dashed line signifies random chance performance (AUC = 0.5), with the True Positive Rate displayed against the False Positive Rate. The suggested ResNet-15 has much superior efficacy compared to alternative models, with an AUC of 0.96, indicating outstanding discriminative abilities in pain assessment. ResNet50 attains an AUC of 0.81, which is commendable, whereas VGG16 earns 0.78, reflecting reasonable effectiveness. The AUCs of CaffeNet and GoogLeNet are 0.70 and 0.65, respectively, showing their subpar categorization abilities. In this comparison, ResNet-15 is the most dependable model for pain assessment, evidenced by its


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enhanced sensitivity and specificity, as indicated by its steep and elevated ROC curve relative to the other models.

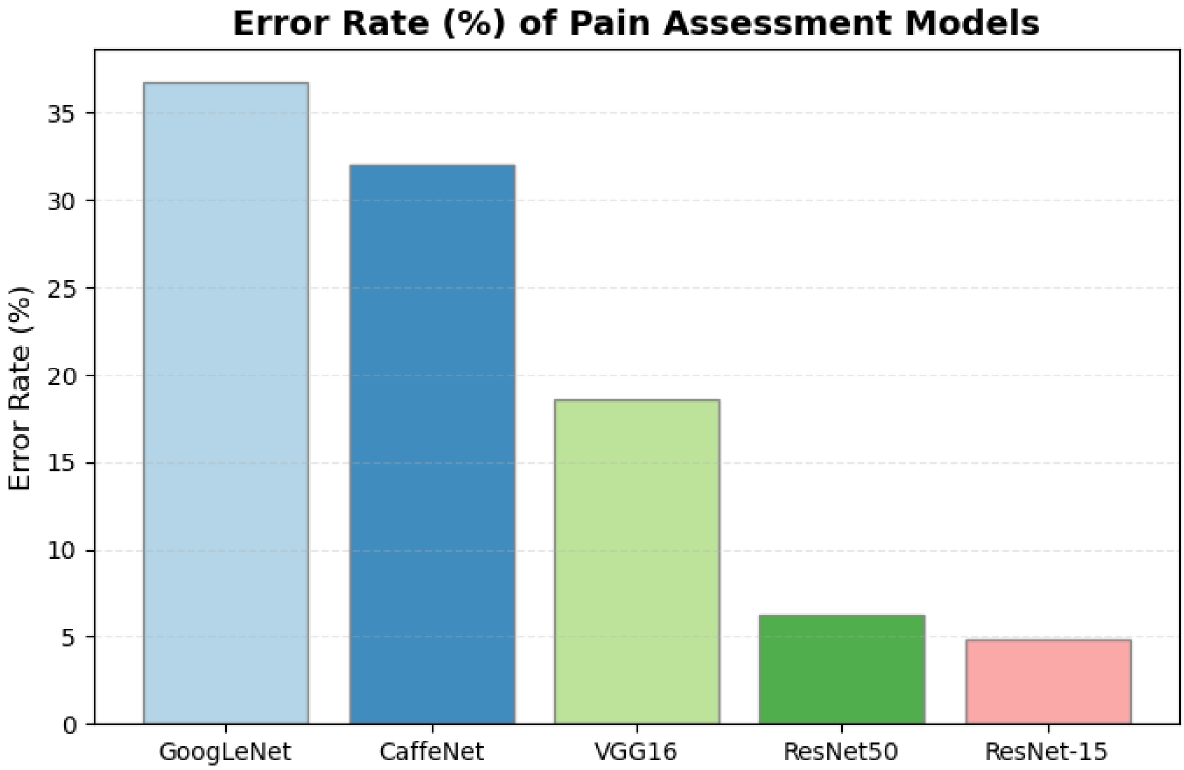


**Fig. 8: Error rate pain assessment Model**

The five pain assessment models—ResNet50, GoogLeNet, CaffeNet, VGG16, and ResNet-15—have their error rates displayed in this bar chart. Among these, GoogLeNet's mistake rate of about 37% is the highest, followed by CaffeNet's error rate of about 32%. With an error rate close to 19%, VGG16 demonstrates a moderate improvement. The error rate is further reduced to approximately 6% using the ResNet50 model, indicating a significant improvement in accuracy. When compared to the other models, the suggested ResNet-15 model has the best performance and reliability in pain assessment, with an error rate of about 5%. The significant improvement in accuracy observed in ResNet-15 compared to GoogLeNet proves that more complex and refined designs are more effective.

## CONCLUSIONS

This ROC curve comparison illustrates the performance of five distinct pain assessment models: GoogLeNet, CaffeNet, VGG16, ResNet50, and the proposed ResNet-15. The diagonal dashed line indicates random chance performance (AUC = 0.5), with the True Positive Rate displayed against the False Positive Rate. The suggested ResNet-15 significantly outperforms the previous models, with an AUC of 0.96, indicating its remarkable discriminative abilities in pain assessment. ResNet50 attains an AUC of 0.81, which is commendable, whereas VGG16 scores 0.78, signifying modest efficacy. The AUCs of CaffeNet and GoogLeNet are 0.70 and 0.65, respectively, showing their subpar categorization abilities. In this comparison, ResNet-



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15 is the most dependable model for pain assessment, evidenced by its enhanced sensitivity and specificity, as indicated by its steep and elevated ROC curve relative to the other models.

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