International Journal of Computing and Digital Systems
ISSN (2210-142X)
Int. J. Com. Dig. Sys. #, No.# (Mon-20..)

Reading Faces, Recommending Choices: A Systematic Review of Facial Emotion Recognition and Recommendation Systems

Dr.Ramesh G[1],Goutham J S[2], Deltan Gleran Lobo[3], Vishma D[4], Mohammed Aman[5]

[1] Dept. of Artificial Intelligence and Machine Learning Alva's Institute of Engineering and Technology Mangalore, India
[2] Dept. of Artificial Intelligence and Machine Learning Alva's Institute of Engineering and Technology Mangalore, India
[3] Dept. of Artificial Intelligence and Machine Learning Alva's Institute of Engineering and Technology Mangalore, India
[4] Dept. of Artificial Intelligence and Machine Learning Alva's Institute of Engineering and Technology Mangalore, India
[5] Dept. of Artificial Intelligence and Machine Learning Alva's Institute of Engineering and Technology Mangalore, India

E-mail address: rameshg@aiet.org.in, goutamsamnekar2031@gmail.com, deltanlobo92@gmail.com, vishmabangera@gmail.com, amanmohdsp@gmail.com

Abstract: This review emphasizes the necessity of intelligent monitoring in our technologically advanced environment by examining the confluence of recommendation systems and facial emotion recognition (FER) model built on CNNs. To increase the model's performance and accuracy, it is trained using a combination of facial photos and "Action Units" (AU), which capture the movement of facial muscles. Particularly for less common emotions like disgust, the article emphasizes how important it is to train with real-world imagery. It presents a feasible pipeline that combines CNN training with face identification and shows how CNNs perform better in FER than Support Vector Machines (SVMs). Comparing the proposed DL model against state-of-the-art algorithms, tests on the JAFFE and FERC-2013 data-sets show that it achieves greater accuracy, computational complexity, detection rate, and learning rate. The CNN architecture and the procedure for gathering data-sets are both thoroughly described by the authors in their paper. They recommend utilizing AUs to better feature extraction by capturing minute facial movements. In comparison to earlier models, the final model which consists of eight conventional layers, pooling, and dropout layers performs better and is especially good at predicting happiness and surprise.Future possibilities for research include adding more real-world photos to the training data-set, adding tiny expressions to the faces, and putting the model on a distributed platform for real-time applications. The possible application of Histogram-Oriented Gradient for real-time face tracking and identification in HCI scenarios is also mentioned in the paper.

Keywords: Facial Emotion Recognition (FER), Recommendation System, Support Vector Machine (SVM), facial expression

1. Introduction

Humans transmit their emotional states mostly through facial expressions. According to studies, nearly 50% of our emotions are conveyed by facial expressions, a tenfold increase above emotions indicated through spoken word intonation. Intelligent monitoring is becoming increasingly vital in everyday living in today's technology-driven networked world. Cameras and assertive robots, for example, must understand human emotions [1]. While humans can easily recognize facial expressions, even the most advanced AI technology find it difficult. There are several challenges to automatic emotion recognition, ranging from emotion categorization to the necessity for more extensive research by psychologists and their partnership with scientists.Body language accounts for 55% of the overall message in face-to-face conversation, whereas words provide only 7%. The manner in which we present the message is critical for understanding the overall scenario. While humans can easily interpret facial expressions, teaching a machine to analyse data and understand

E-mail:goutamsamnekar2031@gmail.com

human emotions in real-time applications presents a substantial hurdle [2]. NLP enables machines to understand some basic verbal communication, but recognize facial expressions will improve their ability to perceive people even more. Human Computer Interaction (HCI) is a broad field that aims to provide the best effective interfaces for applications such as psychological consultations, patient care or healthcare monitoring, rehabilitations, marketing, advertising, video games, movies, music, and education.

A recommender system, also known as a recommendation system or engine, is a sophisticated information filtering tool that predicts and suggests products or material that a user would be interested in based on their interests, behaviours, and prior interactions. These systems serve a critical role in improving user experience across a variety of online platforms, including e-commerce websites, streaming services, and social networking platforms. Using algorithms and data analytics, recommender systems analyse enormous quantities of user data to provide personalised recommendations, assisting consumers in discovering new products, films, music, or other relevant material according to their unique likes [3].

In this paper, we offer a unique CNN model for recognizing facial emotions in real time: sorrow, happiness, anger, surprise, and neutral. The suggested model is trained. In comparison to existing methodologies, our method uses the full face as input rather than geometry- or appearance-based methods. Each pixel in a face is considered a feature, removing the need to connect different facial areas to facial action units.Then these data is taken as input for the recommended system .

1.1 Purpose of the survey

This survey seeks to provide a complete assessment of the convergence of facial emotion recognition (FER) and recommendation systems, as well as to investigate advancements in both domains. With advancements in computer vision and artificial intelligence, integrating FER with recommendation systems poses great potential for elevating user experiences in a variety of applications. The review synthesis existing literature, methodology, and cutting-edge approaches to merging facial emotion analysis with recommendation algorithms [4]. The study provides a holistic knowledge for scholars, practitioners, and industry experts by addressing difficulties, triumphs, and emerging trends at this nexus.It aims to promote future research and innovation in intelligent systems that not only effectively recognise facial expressions but also offers substantial potential for advancing and also utilizing this information to provide personalized recommendations. The work adds to the developing landscape of emotional computing and recommender systems, suggesting prospects for future advances in domains such as e-commerce, entertainment, and mental health [5].

1.2 Motivation

This work investigates the integration of facial emotion recognition (FER) with recommendation systems, bridging artificial intelligence and human emotion comprehension. By incorporating real-time FER, these systems provide a game-changing approach to boosting personalization across domains such as entertainment and mental health support. This invention tackles the limits of existing recommendation systems by giving a deeper understanding of user preferences beyond explicit input. The paper adds to the development of context-aware, emotionally intelligent systems by investigating existing research, obstacles, and future opportunities. The goal is to build a more empathic human-computer interface in which recommendations adjust dynamically to users' emotional states, enabling a personalised and emotionally resonant digital experience [6].

1.3 Organization of paper

This work is organized into five sections: the first is an introduction, the second is a discussion of facial emotion recognition, the third section discussion of recommendation system, fourth section discussion of Machine Learning, fifth is a conclusion and Future Work and fifth is References.

2. RECOMMENDATION SYSTEM

An algorithm or software programme called a recommendation system is made to examine user interactions, preferences, and behaviours with the main goal of recommending items or information to the user. These systems aim to comprehend and anticipate user preferences by utilizing machine learning and data analysis. This allows them to provide customized recommendations that correspond with specific interests. Recommendation systems are mostly useful when they deliver interesting and pertinent items, services, or content to users.Different approaches are used by recommendation system types to accomplish this customized strategy. In contrast to content-based filtering, which concentrates on item attributes and user preferences, collaborative filtering depends on user interactions and commonalities across users [7]. Hybrid systems integrate various methods to provide a recommendation technique that is more thorough. Furthermore, in order to improve recommendations, knowledge-based recommendation systems take explicit information about users and goods into account.

Recommendation systems' ongoing development is essential to maximizing user interaction and content discovery on a variety of online platforms.Online content providers, social media platforms, streaming services, e-commerce, and other industries all make extensive use of recommendation algorithms. These systems help consumers find new products or services that fit their tastes in e-commerce, for example, so they may make better informed purchases. Recommendation algorithms are utilised by streaming companies to provide personalised recommendations for films, music, or TV series, hence increasing user satisfaction and retention [8]. The on going development of recommendation systems is characterised by the investigation of sophisticated methods like reinforcement learning and deep learning, which seek to identify more complex patterns in user behaviour in order to produce predictions that are even more accurate. Emerging study areas that address the need for users to comprehend and trust the advice offered are explainability and transparency in recommendations.

Recommendation system integration with cutting-edge technologies like virtual reality and augmented reality shows potential for providing immersive and customized experiences as technology advances. In the quickly changing digital landscape, recommendation systems play a critical role in improving user engagement, customisation, and overall satisfaction. This is demonstrated by the continual research and development in this field [8].

The following are the primary categories:

i. Suggestions Based on Content: Suggests products based on what the user has manifested interest before. Compares the item's content with the user's preferences after analysing it. Ideal in situations with clearly defined user preferences.

ii. Teamwork in Filtering: Suggests products based on users' like-minded interests and actions. uses information about user-item interactions to find trends and forecast future events.It works well in situations where user preferences are vague Issues with Recommendation Systems.The cold start problem, which makes it hard to make recommendations for new users or objects with little data, is one of the stumbling points in developing successful recommendation systems. It is also an ongoing effort to strike a balance between diversity and accuracy in recommendations.

iii. Mechanism of Operation: Generally, recommenda-tion systems function in three stages:

a. Information Gathering: Compile information about user interactions, preferences, and behaviours with the items includes both explicit and implicit feedback, such as ratings and reviews and clicks and views.

b. Modelling: Create models by analysis the gathered data using algorithms. Item features are the main emphasis of content-based models, whereas user-item interactions are used in collaborative filtering models.

c. Formulating Recommendations: Create user-specific recommendations by utilizing the pre-existing models.

Items that match the user's preferences are recommended by content-based systems, whereas collaborative filtering systems propose deliver suggestions influenced by the choices of other users.

1.3 Uses for Recommendation Systems

In many different fields and sectors, recommendation systems are essential.

i. Online Shopping: Make product recommendations depending on the user's past purchases and browsing activities.Boost customer happiness and sales.

ii. Streaming Platforms: Based on the user's tastes, suggest films, TV series, or music.
Increase user loyalty and engagement.

iv. Social Media: On the basis of user activity, recommend connections, posts, or groups.Boost user communication and involvement.

v. Platforms for news and content: Based on your reading preferences, suggest articles, blogs, or videos.Improve content discovery and user experience.

vi. Journey and Received Hospitality: Provide travel options, lodging options, or things to do based on personalized suggestions according to the user's choices.
Enhance client happiness by personalizing travel experiences.

3. Facial Expression Recognition

Facial Expression Recognition (FER) In the cutting-edge fields of computer vision and artificial intelligence, facial emotion recognition, or FER, focuses on identifying and comprehending human emotions from facial expressions. FER aims to close the gap between computational understanding and human communication by bringing together psychology, machine learning, and image processing.FER relies heavily on its capacity to read facial expressions and characteristics to identify emotional states. While humans can read faces with ease, teaching machines to do the same requires intricate algorithms and large amounts of data. FER systems usually start with a technique called face detection, which finds faces in pictures or video frames [9]. Mapping the shape of the face and identifying important facial landmarks are the first steps in this process.FER's ability to detect subtle emotional changes is what makes it so important. While rule-based systems and manually created features were the main focus of traditional approaches, more recent developments have made use of deep learning, specifically Convolutional Neural Networks (CNNs). More sophisticated and precise emotion recognition is made possible by CNNs' ability to automatically develop hierarchical representations from raw pixel input [10].

Happiness, sorrow, anger, surprise, fear, and disgust are some of the main facial expressions that are frequently linked to different emotions. Particular face muscle shapes and motions correspond with each emotion. For example, enjoyment is characterised by a smile, whereas astonishment is shown by widened eyes and raised eyebrows. FER algorithms examine these facial expressions to deduce a person's emotional state. In order to train strong FER models, data is essential. Especially important for supervised learning are data-sets containing labelled faces with corresponding emotions [11]. These data-sets are used by scientists and programmers to train models that identify trends and correlations between emotions and facial characteristics. The improvement of FER algorithms is facilitated by ongoing improvements in data-set size, diversity, and quality.

Key facial expressions often studied include happiness, sadness, rage, surprise, fear, and disgust as shown in figure 1.

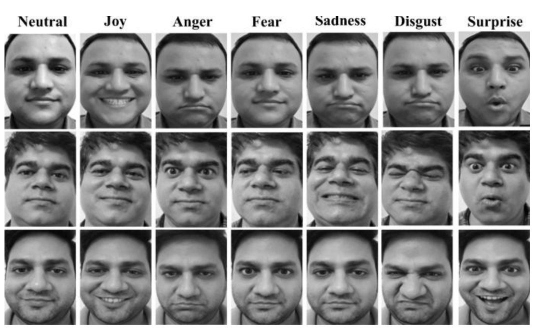

Figure 1. Different facial expressions

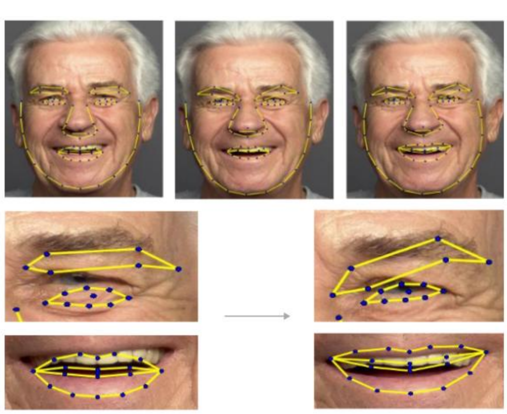

Figure 2. Face points marking

Figure 2 shows typical face recognition workflow, face landmarking is the first step. The precise location of facial landmarks, such as the nose tip, the corners of the eyes, and other distinguishing features, in facial images is an important process. Accurately identifying landmarks is crucial for face alignment because it acts as a prelude to feature extraction, which is necessary for later steps in the face recognition pipeline.

The technique normally entails taking or analysing pictures or video frames of a person's face to extract facial traits like the position of the eyes, lips, and overall facial muscle movements. Machine learning algorithms, which are frequently trained on labelled data-sets, are then utilised to recognise patterns associated with various emotions [12]. FER has many different and wide-ranging real-world applications. With the help of FER capabilities, social robotics devices can communicate with people more naturally and react to their emotional states accordingly. Through the ability of systems to adjust in response to emotions identified, FER improves user experiences in human-computer interaction. For example, when a learner displays signs of impatience, an instructional programme may modify its methodology.

Beyond specific uses, recommendation systems and FER interact, especially in the e-commerce and entertainment industries. Recommendation algorithms that measure users' emotional responses might make recommendations for products or content that match the user's current mood. By giving consumers more pertinent and emotionally impactful recommendations, this integration improves personalization [13]. The effects of FER are felt in the healthcare industry, as it facilitates mental health monitoring. FER systems, which analyse facial expressions, have the potential to aid in the early detection of mood disorders and facilitate the monitoring of treatment outcomes. FER is also used in autism research, understanding the facial expressions of people with autism spectrum disorders to help carers and other professionals better understand and support them [14].

FER is not without difficulties, despite its progress. There are challenges developing universal models due to the diversity of facial emotions across genders, ages, and cultures. Additionally, it is crucial to address ethical issues like consent and privacy while collecting facial emotion data. A key focus in the development of FER continues to be striking a balance between ethical concerns and technological advancement.

There are a lot of intriguing things that FER may do in the future. Higher accuracy and greater adaptability are anticipated from FER systems as technology develops further. A deeper comprehension of human emotions is anticipated through the integration of multimodal techniques, which combine gesture and speech recognition with facial analysis [15].

4. Logistic Regression

The foundation tool of logistic regression plays a vital role in the complex interplay between recommendation systems and face emotion recognition. Recommendation systems can be better equipped to provide personalized content by using this statistical technique to predict and classify a user's emotional states. Using complex facial features and comprehending how they relate to different emotions in subtle ways is key.As the crucial link between the visible facial traits and the underlying emotional states, logistic regression works. Logistic regression gains the ability to identify patterns and relationships in this complicated data by means of training on labeled data-sets, wherein facial expressions are linked to particular emotions. The final model encapsulates the probability distribution of a user experiencing each emotion by transforming face features across different emotions.In order to provide a complex knowledge of emotions, logistic regression's probabilistic aspect is crucial. More precisely, the model provides a continuous spectrum of probabilities as opposed to only discrete labels, enabling a more detailed depiction of the user's emotional terrain [16].

In a dynamic recommendation system, the real power of logistic regression emerges when this probability distribution is used to customize recommendations. The logistic regression model continuously analyses the user's facial expressions as they interact with the information, dynamically adjusting its predictions in real time. As a result, the user experience is seamless and customized, and the recommendation system is kept aware of the user's changing emotional states. Recommendation systems get an additional dimension when face emotion recognition and logistic regression are combined; this new dimension is sensitive to the sentiment of the user. The system can now curate material based on the user's present emotional state in addition to past preferences and explicit user feedback thanks to this synergy. In order to increase engagement and happiness, a user who exhibits signals of delight, for example, can be directed towards content that reflects this feeling.
Generally Logistic Regression takes more than 2 input i.e x1,x2,x3 and produces output according to which it belongs to. As shown in the Figure 3.

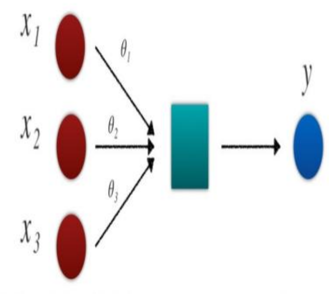

Figure 3. General Logistic Regression Model

Logistic regression, in its simplest form, serves as a link between the dynamic terrain of user emotions and recognized facial cues. It converts unprocessed facial data into actionable insights and creates a journey that is both immersive and user-centric by integrating smoothly into recommendation systems. The combination of emotion and recommendation enhances user experience and highlights how technology can be quickly and effectively adapted to understand and address the nuances of human emotion.

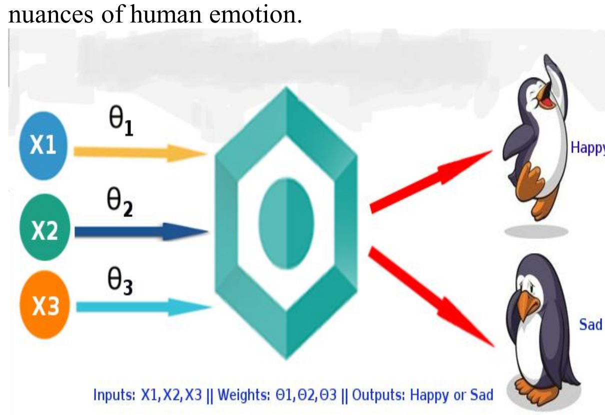

Figure 4. Logistic Regression Model For Emotion Classification

Figure 4 is Logistic Regression Model specific to Emotion Classification used in Emotion recognition.

The mathematical formulation of the LR algorithm is presented as follows:

$$P = \frac{1}{1 + e^{-(a+bX)}} \tag{1}$$

Where

- a+bX = z
- P-Probability of the data instance lying in a classified class

- z is a linear combination of the independent variables and their coefficients.

The above could also be represented in the form

$$ln\left(\frac{p}{1-p}\right) = b0 + b1 * X \tag{2}$$

The integration of logistic regression into this procedure looks like this:
i.Feature Extraction: The first stage entails taking pertinent features from expressions on the face. These characteristics could be expressions, landmarks on the face, or other facial descriptors. The logistic regression model uses these characteristics as input variables (X).
ii.Labelling and Training: A labelled data-set is necessary for logistic regression to function. The data-set includes examples of facial expressions that have been labelled with the appropriate emotions (e.g., happy, sad, surprised). After that, this data-set is used to train logistic regression, where the independent variables are the facial features and the dependent variable (Y) is the emotion labels.
iii. Probability Prediction: Using a user's facial features as a guide, the logistic regression model can ascertain the likelihood that a given emotion will be experienced by them. By using the logistic function, a probability score between 0 and 1 is produced from the linear combination of features and weights.
iv. Thresholding: The predicted emotion class is ascertained by applying a threshold to the predicted probabilities. Probabilities greater than or equal to 0.5, for instance, may be classified as one emotion, and probabilities less than 0.5, as another. This is the case, for example, if the threshold is set at 0.5. For continuous probabilities to be converted into discrete emotion labels, this thresholding step is essential.
v. Recommendation System Integration: The suggested system is then updated with the logistic regression model's output, which depicts the anticipated emotion. Utilizing this emotion label, the recommendation algorithm customizes recommendations according to the user's emotional condition. For example, if the system predicts that the user is happy, it may suggest content that is upbeat or joyful.
vi. Real-time Adaptation: One of logistic regression's advantages is its computational effectiveness, which qualifies it for real-time use. The logistic regression model can dynamically modify its predictions in response to changes in a user's facial expressions, enabling the recommendation system to dynamically modify its suggestions in response to the changing emotional context [17].

5. Machine Learning

Intelligent machines can learn from experience and become smarter without explicit programming thanks to machine learning (ML), a dynamic subset of artificial intelligence. Fundamentally, machine learning (ML) computers replicate how humans learn by analyzing data patterns, spotting trends, and making deft judgments or predictions. Labeled data-sets are used for model training in supervised learning, whereas unlabeled data is used in unsupervised learning to find patterns. The method of decision-making used in reinforcement learning is reward-based. Applying machine learning (ML) to a variety of fields, such as natural language processing and picture identification, shows how versatile the technology is.The capacity of ML models to generalize learning to new, unknown data is a critical component for solving problems in the real world and determines how effective the models are. Deep learning and neural network developments are enabling automation, tailored suggestions, and data-driven insights through machine learning (ML), which is reshaping businesses and bringing about a paradigm shift in the way technology is used [18].

5.1 SVM

Classification and regression tasks benefit significantly from the use of Support Vector Machine(SVM). The aim of SVM is to devise a hyper-plane that efficiently separates the data points of distinct classes in a high-dimensional space. The focus is on maximizing the margin, characterized by the distance between the hyper-plane and the closest data point.In a binary classification scenario, SVM seeks the ideal hyper-plane that not only separates the classes but also assures the highest separation margin. SVM is highly effective in high-dimensional spaces and is capable of managing both linear and non-linear correlations between features. To handle non-linear data, it can utilize kernel functions to map input features into higher-dimensional spaces [19]. SVMs are widely employed in a variety of applications, including image classification, text categorization, and bio-informatics, due to their environment to handle complicated decision boundaries and generalize well to unknown data. SVM performance is highly dependent on the kernel function and tuning parameters, especially the Margin parameter C. Finding a hyper-plane that successfully divides complex patterns becomes simpler when using kernel functions to convert the input data into a higher-dimensional space for SVM. SVM is able to capture complex decision boundaries through this transformation that would be challenging to accomplish in the original feature space. Since it defines how well the transformation works, the kernel and its parameters have a big impact on SVM performance. SVM's capacity to achieve a smooth decision boundary and correctly categories training data depends critically on the tuning parameters, such as the Margin parameter (C). A lower C number prioritizes generalization to new, unknown data and encourages a larger margin, whereas a higher C value leads to a narrower margin but may result in a better fitting of the training set. Due to its versatility, Support Vector Machines (SVM) are widely used in image recognition, text classification, and bio-informatics, among other domains. Its significance in machine learning and data analysis is highlighted by its wide range of applications, which also contribute to its continued popularity and adoption in various fields. SVM is a preferred choice in scenarios where data complexity requires a sophisticated approach because of its ability to handle high-dimensional data, robustly separate classes, and accommodate non-linear relationships. The regularization parameter, typically designated as C in Support Vector Machines (SVM), acts as a hyper parameter managing the balance between attaining minimal training error and low testing error. This parameter has a large impact on the SVM's decision boundary, as it determines the penalty for misclassifying training data [20]. Figure 5 shows how the SVM processes an image and labels it.

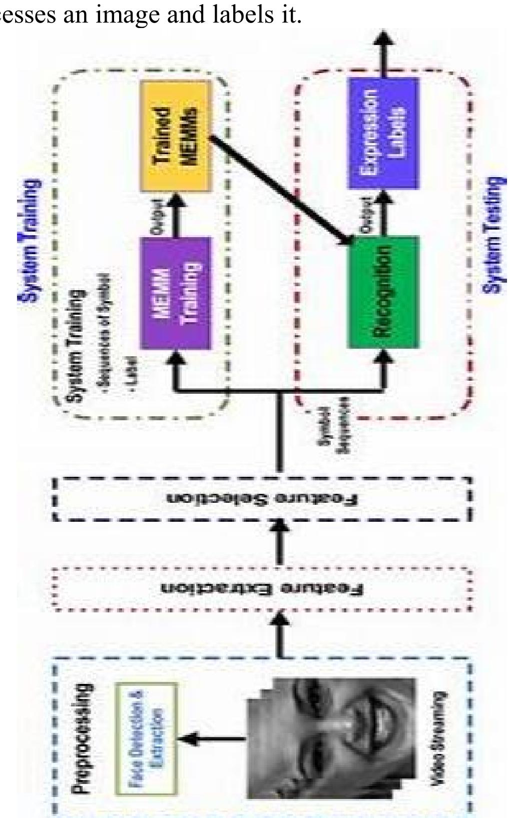

Figure 5. FER in SVM

A lower C value yields a wider margin, allowing some training integral points to be misclassified and providing a more flexible model. A higher C, conversly, imposes a stronger penalty for misclassification, resulting in a narrower margin and a more rigid model that closely matches the training data [20].

Essentially, the regularization parameter prevents over-fitting by controlling the trade-off between model complexity and its competence to generalize to new, previously unknown data. Selecting an appropriate regularization value is critical for fine-tuning SVM models to ensure optimal performance on individual data sets, striking the proper balance to permit robust generalization without being unduly impacted by noise or outliers amidst the training data [21]. In the below Figure 6 by using some parameters the data is classified in two classes i.e class1 and class 2.

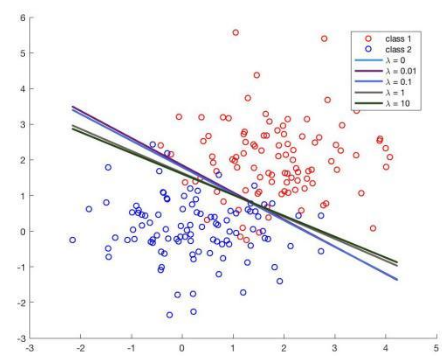

Figure 6. Regularization parameter in SVM

The margin or gap is a critical notion in Support Vector Machines (SVM). This gap signifies the distance between the decision boundary and the nearest data point of any class. SVM's objective is to locate the hyper-plane that maximizes this margin, resulting in a robust and well-generalized classification. The margin is modified by a parameter also known as the "Margin parameter" or "C" in SVM. This value strikes a balance between achieving a greater margin and minimizing classification mistake [22].

The data is classified using margin parameters as class 1 and class 2 as shown in the Figure 7. The maximum width possible for the class boundary is represented by the margin. In order to improve its capacity to efficiently generalize to unobserved data, SVM looks for a hyper-plane that maximizes this margin. Additionally, because they represent the data points closest to the decision boundary, the support vectors are essential in controlling the margin width.

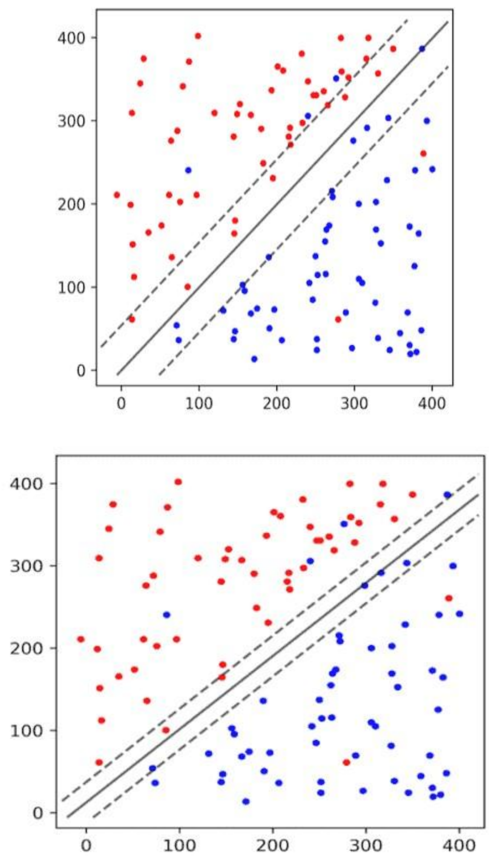

Figure 7. Margin parameter in SVM

5.2 Methodology

Facial Emotion Recognition (FER) has recently received plenty of attention because of the potential applications in areas such as human-computer interaction, virtual reality, and emotion-aware computing. The current study looks into various machine learning methodologies for enhancing the accuracy and efficiency of FER systems.

In the field of facial emotion recognition, Support Vector Machines (SVMs) and Convolutional Neural Networks (CNNs) emerge as prominent performers. SVMs are well-suited for categorizing face expressions owing to their adeptness in handling high-dimensional data and produce explicit decision bounds. CNNs, on conversely, are inspired by the human visual system and excel in learning hierarchical characteristics from photographs automatically, allowing them to capture intricate patterns within facial data [23].

The paper offers Linear Discriminant Analysis (LDA) as a valuable tool, especially when categorizing emotions into more than two groups. LDA, a dimensionality reduction method, enables the transformation of the original feature space into a lower-dimensional one while preserving class separability. This is especially beneficial in circumstances requiring sophisticated distinctions between multiple emotions.

Vectorization of facial images is a vital step in translating complex visual data within a machine learning-friendly format. The study stresses the vitality of this stage in enhancing the model's discriminative ability.

The SVM is fed labeled training data throughout the training phase, allowing it to learn the numerous attributes associated with each emotion. The efficiency of the trained model is subsequently scrutinized using test images, providing information into its generalization capabilities.

The paper's practical application is a rigorous strategy for recognizing facial expressions. This entails collecting frames from a webcam, which is an important initial step in obtaining raw data. Following that, human faces are recognized inside these frames utilizing algorithms that assure proper facial feature localization [24].

The proposed method of facial expression recognition (FER) integrates insights from various research articles and reviews and provides a comprehensive framework that could be applied in various fields. This method includes key components such as face representation, feature extraction, classification and practical implementation steps, providing a versatile platform for eHealth, social IoT, emotional intelligence and cognitive AI applications.

A. System parts and purposes:

Components: FERS includes face representation, feature extraction and classification components. Objective: to predict facial expressions (fear, anger, happiness) based on embedded facial images.

B. Application steps:

- Pretreatment: Uses a wooden sub-model to detect and extract the face region. Ensures standardization through resizing and normalization. Separation of functions: Uses deep CNN models for robust feature extraction. Uses global general functions of CNN, larger image resizing and learning to improvise the presentation. Classification: Predicts the sense of facial expression with a focus on overcoming excess problems. Includes interrupt management and optimization techniques.
- Pretreatment of the face: Applies a deep learning framework to recognize different human facial expressions. Uses a wooden partial model to find facial landmarks.
- Representation of functions to classify expressions: Extracts distinctive features using advanced CNN architectures. Improve performance with image up-

scaling, fine-tuning, incremental re-sizing and transfer learning.

- Proposed CNN Architecture: Builds CNN models (CNN1, CNN2 and CNN3) with different input image resolutions. Defines layers, output formats, image sizes and parameters for each architecture.
- Factors affecting performance: Data Augmentation: Augments training samples using techniques such as rotation, blurring, and denoising.
- Fine-tuning: Adjusts and retrains specific levels to improve relevance. Incremental
- Re-sizing: Improves generalization through successive practice with progressively larger image sizes. Transfer learning: Speeds up training and potentially reduces generalization errors by using pre-trained model weights.
- Scores Fusion: Combines classification scores from different CNN architectures to improve accuracy.
- Optimization: Uses stochastic optimization methods for training, specifically the Adam optimizer.

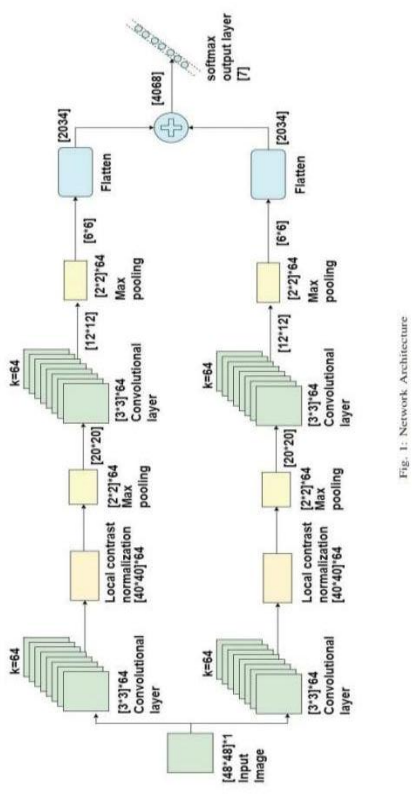

Figure 8. Network Architecture

5.3 Basic CNN

Convolutional Neural Networks (CNNs) have become a key component in facial recognition technology, transforming how computers interpret and process visual information. Because of their special architecture designed for image processing tasks, CNNs are essential in face recognition applications. The network is made up of convolutional layers that use the input image to automatically learn hierarchical representations of features including edges, textures, and patterns. CNNs are skilled at catching minute facial details because of this feature [25].

CNNs are superb for extracting discriminative traits that set one face apart from another in the field of face recognition. To capture spatial hierarchies and local information in the input image, the convolutional layers convolve over it using filters. CNNs can detect faces with robustness in a variety of scenarios, including variations in illumination, posture, or facial emotions, thanks to their capacity to distinguish features at different sizes.Additionally, CNNs may be trained on big data-sets, which enhances their ability to generalise to a wide range of facial features. Efficiency and accuracy are increased using transfer learning, which involves optimising pre-trained models on large data-sets for particular face recognition tasks [26].

CNNs are being used in facial recognition for purposes other than security; these include emotion analysis, personalized user experiences, and human-computer interaction. CNNs remain in the vanguard, demonstrating their aptitude for comprehending and interpreting complicated visual data for precise and effective face detection, as the need for trustworthy facial recognition systems increases [27].

5.4 Application

1.Recommendations for Entertainment Content: FER can be used to analyse user emotions when watching movies or videos.

Recommend content based on emotional reactions to ensure personalized choices fit with the viewer's emotional preferences.

2.Platforms for E-Learning: Incorporate FER into online learning platforms to assess student emotions during lessons.

Recommendation: Tailor educational content and suggestions on the basis of emotional engagement of the learner, creating an adaptive and successful learning experience.

3.Product Suggestions for E-Commerce: Use FER to analyse client emotions while shopping for products.

Recommendations:

Make product recommendations based on emotional responses to magnify the chances of satisfying the customer's preferences and wants.

4.Apps for Health & Wellness:Integrate FER with health and wellness applications to track users' emotional states.
Recommendation: Depending on the user's emotional requirements and fluctuations, suggest personalized well-being activities, stress-relief approaches, or mindfulness exercises.

5.Recommendations for Music and Playlists: Utilize FER to analyse consumers' emotional states while listening to music.
Recommendation: Curate playlists based on observed emotions, providing a personalized audio experience that matches the user's mood.

6. Experiences with Augmented Reality: Use FER in apps involving Augmented Reality to measure users' emotional reactions to virtual environments. Using the emotions that have been identified, suggest interactive features or changes to the information in the augmented environment to make the experience more interesting and unique.

7. Travel and Tourism: Use FER to examine users' feelings while they browse through potential destinations in travel applications. Adapt travel suggestions such as places to visit, places to stay, and things to do according to the emotional preferences conveyed by facial expressions, thus improving the whole trip planning experience.

8. Social Media Sites: To comprehend users' emotional states during conversations, apply FER to social media platforms. Improve the platform's recommendation system to make recommendations for engaging techniques, relationships, or relevant information depending on the emotions identified, promoting deeper and more pleasurable social interactions.

9. Culinary Suggestions: Apply FER in recipe and food applications to examine customers' feelings as they peruse menu items. To provide a more engaging and pleasurable culinary experience, provide tailored recipe suggestions and preparation advice based on the identified emotions.

10. Services for Financial Advisory: Incorporate FER with financial applications to gauge users' emotional moods when making investments or financial plans. To help consumers make better financial decisions and enhance their overall well-being, offer tailored financial advice, investment ideas, or budgeting guidelines depending on the emotions identified.

11. Job-Seeking Websites: Apply FER to job search applications to learn about users' emotional reactions to job advertisements. Improve the recommendation system so that it makes suitable employment recommendations, career guidance, or skill-development resources based on the emotions identified, thereby streamlining the hiring process.

6. Conclusion And Future work

The paper gives a thorough introduction to deep learning-based facial emotion recognition (FER), with a particular emphasis on data-sets and techniques. It highlights how crucial images of the natural world are for training, particularly for less prevalent emotions like disgust. CNN outperforms SVM in FER, as demonstrated by a working pipeline that combines CNN training with face detection. When tested on the JAFFE and FERC-2013 data-sets, the suggested DL model surpasses in performance than the state-of-the-art algorithms with respect to accuracy, computational complexity, detection rate, and learning rate.

The authors describe their work in depth, breaking it down into two primary sections: CNN building and data-set gathering. They propose using "Action Units" over the course of time to record the movement of the face's muscles in order to recognize features.
With eight conventional layers, pooling, and dropout layers, the final model surpasses earlier models in performance and is particularly good at predicting pleased and surprised emotions. Future possibilities for study include adding more real-world photos to the training data-set, adding small facial expressions, and moving the model to a distributed platform for real-time applications like customer experience surveys at shopping centres. Additionally, a global strategy for feature extraction utilising Histogram-Oriented Gradient is covered in the research for real-time face identification and tracking in machine interaction contexts in addition to online proctoring systems.

The research also presents a face recognition system that emphasizes its enhanced performance despite being time-consuming. It is built on CLAHE, HOG features, and SVM classifier. When compared to alternative machine learning techniques, the suggested algorithm shows improved face recognition productivity and accuracy.

This work's main goal was to showcase a thorough examination of deep learning, including every stage from acquiring data-sets to analyzing the results. The two primary parts of the exploration were managing the data-set and building the CNN (Convolutional Neural

Network). The authors suggest using the same data-set for future experiments, but adding "Action Units" to record facial muscle activity as features, therefore improving the CNN input. They advise utilizing a computer with appropriate specs, especially one with a strong Graphics Processing Unit (GPU), to enable quick and effective parameter experimenting.The futuristic and comparatively uncharted nature of face recognition is also highlighted in the study, with a focus on its numerous real-world applications in fields like criminal investigations and security.

REFERENCES

[1] Lasri, Imane, Anouar Riad Solh, and Mourad El Belkacemi. "Facial emotion recognition of students using convolutional neural network." 2019 third international conference on intelligent computing in data sciences (ICDS). IEEE, 2019.

[2] Kartali, Aneta, et al. "Real-time algorithms for facial emotion recognition: A comparison of different approaches." 2018 14th Symposium on Neural Networks and Applications (NEUREL). IEEE, 2018.

[3] Gervasi, Osvaldo, et al. "Automating facial emotion recognition." Web Intelligence. Vol. 17. No. 1. IOS Press, 2019.

[4] Hayes, Grace S., et al. "Task characteristics influence facial emotion recognition age-effects: A meta-analytic review." Psychology and Aging 35.2 (2020): 295.

[5] Wang, Xiaohua, et al. "Laun improved stargan for facial emotion recognition." IEEE Access 8 (2020): 161509-161518.

[6] Mehendale, Ninad. "Facial emotion recognition using convolutional neural networks (FERC)." SN Applied Sciences 2.3 (2020): 446.

[7] Khaireddin, Yousif, and Zhuofa Chen. "Facial emotion recognition: State of the art performance on FER2013." arXiv preprint arXiv:2105.03588 (2021).

[8] Jain, Deepak Kumar, Pourya Shamsolmoali, and Paramjit Sehdev. "Extended deep neural network for facial emotion recognition." Pattern Recognition Letters 120 (2019): 69-74.

[9] Mellouk, Wafa, and Wahida Handouzi. "Facial emotion recognition using deep learning: review and insights." Procedia Computer Science 175 (2020): 689-694.

[10] Giannopoulos, Panagiotis, Isidoros Perikos, and Ioannis Hatzilygeroudis. "Deep learning approaches for facial emotion recognition: A case study on FER-2013." Advances in Hybridization of Intelligent Methods: Models, Systems and Applications (2018): 1-16.

[11] Pranav, E., et al. "Facial emotion recognition using deep convolutional neural network." 2020 6th International conference on advanced computing and communication Systems (ICACCS). IEEE, 2020.

[12] Alreshidi, Abdulrahman, and Mohib Ullah. "Facial emotion recognition using hybrid features." Informatics. Vol. 7. No. 1. MDPI, 2020.

[13] Jain, Neha, et al. "Hybrid deep neural networks for face emotion recognition." Pattern Recognition Letters 115 (2018): 101-106.

[14] Reddy, Chirra Venkata Rami, Uyyala Srinivasulu Reddy, and Kolli Venkata Krishna Kishore. "Facial emotion recognition using NLPCA and SVM." Traitement du Signal 36.1 (2019): 13-22.

[15] Shaees, Shamoil, et al. "Facial emotion recognition using transfer learning." 2020 International Conference on Computing and Information Technology (ICCIT-1441). IEEE, 2020.

[16] Saleem, T. and Chishti, M., 2020. Assessing the efficacy of logistic regression, multilayer perceptron, and convolutional neural network for handwritten digit recognition. *International Journal of Computing and Digital Systems*, *9*(2), pp.299-308.

[17] Srimaneekarn, N., Hayter, A., Liu, W. and Tantipoj, C., 2022. Binary response analysis using logistic regression in dentistry. *International Journal of Dentistry*, *2022.*

[18] Jiang, Ming, et al. "Classifying individuals with ASD through facial emotion recognition and eye-tracking." 2019 41st Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC). IEEE, 2019.

[19] Haddad, Jad, Olivier Lézoray, and Philippe Hamel. "3d-cnn for facial emotion recognition in videos." Advances in Visual Computing: 15th International Symposium, ISVC 2020, San Diego, CA, USA, October 5–7, 2020, Proceedings, Part II 15. Springer International Publishing, 2020.

[20] A. Narayanan, S. Verma, E. Ramadan, P. Babaie, Z.-L. Zhang, Deepcache: A deep learning based framework for content caching, in: Proceedings of the 2018 Workshop on Network Meets AI & ML, 2018, pp. 48–53.

[21] S.O. Somuyiwa, A. György, D. Gündüz, A reinforcement-learning approach to proactive caching in wireless networks, IEEE J. Sel. Areas Commun. 36 (6) (2018) 1331–1344.

[22] A. Ndikumana, N.H. Tran, K.T. Kim, C.S. Hong, et al., Deep learning based caching for self-driving cars in multi-access edge computing, IEEE Trans. Intell. Transp. Syst. 22 (5) (2020) 2862–2877.

[23] M.A. Naeem, T.N. Nguyen, R. Ali, K. Cengiz, Y. Meng, T. Khurshaid, Hybrid cache management in IoT-based named data networking, IEEE Internet Things J. 9 (10) (2021) 7140–7150.

[24] Dalvi, Chirag, et al. "A survey of ai-based facial emotion recognition: Features, ml & dl techniques, age-wise data-sets and future directions." Ieee Access 9 (2021): 165806-165840.

[25] Akhand, M. A. H., et al. "Facial emotion recognition using transfer learning in the deep CNN." Electronics 10.9 (2021): 1036.

[26] Modi, Shrey, and Mohammed Husain Bohara. "Facial emotion recognition using convolution neural network." 2021 5th International Conference on Intelligent Computing and Control Systems (ICICCS). IEEE, 2021.

[27] B. Banerjee, A. Kulkarni, A. Seetharam, Greedy caching: An optimized content placement strategy for information-centric networks, Comput. Netw. 140 (2018) 78–91.

[28] Z. Zhang, C.-H. Lung, I. Lambadaris, M. St-Hilaire, IoT data lifetime-based cooperative caching scheme for ICN-IoT networks, in: 2018 IEEE International Conference on Communications, ICC, IEEE, 2018, pp. 1–7.

[29] X. Cao, J. Zhang, H.V. Poor, An optimal auction mechanism for mobile edge caching, in: 2018 IEEE 38th International Conference on Distributed Computing Systems, ICDCS, IEEE, 2018, pp. 388–399.

[30] Nirmala Sreedharan, Ninu Preetha, et al. "Grey wolf optimisation-based feature selection and classification for facial emotion recognition." IET Biometrics 7.5 (2018): 490-499.

[31] Arora, Malika, Munish Kumar, and Naresh Kumar Garg. "Facial emotion recognition system based on PCA and gradient features." National Academy science letters 41 (2018): 365-368.

[32] wSelinger, Evan, and Woodrow Hartzog. "The inconsentability of facial surveillance." Loy. L. Rev. 66 (2020): 33.

[33] Naga, Prameela, Swamy Das Marri, and Raiza Borreo. "Facial emotion recognition methods, data-sets and technologies: A literature survey." Materials Today: Proceedings 80 (2023): 2824-2828.

[34] Khattak, Asad, et al. "An efficient deep learning technique for facial emotion recognition." Multimedia Tools and Applications (2022): 1-35.

[35] Krause, Fernando C., et al. "Facial emotion recognition in major depressive disorder: A meta-analytic review." Journal of affective disorders 293 (2021): 320-328.

[36] Sarvakar, Ketan, et al. "Facial emotion recognition using convolutional neural networks." Materials Today: Proceedings 80 (2023): 3560-3564.

[37] Cabitza, Federico, Andrea Campagner, and Martina Mattioli. "The unbearable (technical) unreliability of automated facial emotion recognition." Big data & society 9.2 (2022): 20539517221129549.

[38] Arora, Malika, and Munish Kumar. "AutoFER: PCA and PSO based automatic facial emotion recognition." Multimedia Tools and Applications 80 (2021): 3039-3049.

AUTHORS PROFILE

Dr.Ramesh G is currently working as a professor in the Department of Artificial Intelligence and Machine Learning, Visvesvaraya Technological University (VTU) , Belagavi. He has completed his B.E and M.Tech from Vishveswaraya Technological University (VTU), Karnataka. All the degrees are in Computer Science and Engineering (CS&E) discipline. He has published papers in International Reputed Journals and International Conferences. He has attended various FDP programs. His current research lies in the areas of Image Processing, Machine learning, Deep learning.

Goutham J S is currently pursuing a Bachelor's degree in Artificial Intelligence and Machine Learning at Alva's Institute of Engineering and Technology (AIET) , affiliated with Visvesvaraya Technological University (VTU) in Karnataka. He is intersted in research fields like Machine Learning , Data Science, DeepLearning,Artificial Intelligence. Demonstrating a commitment to these revolutionary field's knowledge advancement and innovation-fostering.

Deltan Gleran Lobo is currently pursuing a Bachelor's degree in Artificial Intelligence and Machine Learning at Alva's Institute of Engineering and Technology (AIET),affiliated with Visvesvaraya Technological University (VTU) in Karnataka. His academic focus extends to a keen interest in areas like Web Technologies, Natural Language Processing (NLP), Cloud Computing,Deep Learning , Machine Learning, and Data Science, showcasing a dedication to advancing knowledge and fostering innovation in these transformative fields.

Mohammed Aman is presently dedicated to the pursuit of a Bachelor's degree in Artificial Intelligence and Machine Learning at Alva's Institute of Engineering and Technology (AIET), affiliated with Visvesvaraya Technological University (VTU) in Karnataka. His scholarly focus extends to profound interests in research domains such as Machine Learning, Data Science, and Deep Learning Intelligence, reflecting a commitment to advancing knowledge and innovation in these transformative fields.

Vishma D is currently pursuing Bachelor's of degree in Artificial Intelligence and Machine Learning at Alva's Institute of Engineering and Technology (AIET), affiliated with Visvesvaraya Technological University (VTU) in Karnataka. She has a keen interest in domains such as Machine Learning and Data Science.