Deep Learning-Based Emotion Detection in Elderly Individuals

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Abstract: Amidst global demographic shifts, many nations are transitioning into aging societies, posing significant challenges to elderly mental health. This vulnerable demographic necessitates close attention and specialized care. Among the pivotal concerns is mental well-being, where technology plays a crucial role. Facial Expression Recognition (FER) emerges as a promising tool for assessing elderly emotions, vital for effective mental health support. In the realm of human-computer interaction, emotion recognition empowers computers to anticipate human emotional states through observation, facilitating emotionally responsive communication. This project proposes a comprehensive reminder system tailored for elderly care, streamlining medication management, doctor appointments, and caregiver notifications. Leveraging deep learning techniques, the system discerns elder emotions, enabling swift caregiver responses. Built on the Django framework with MySQL for data storage, the accompanying Android application furnishes an intuitive interface for user interaction.

1. Introduction :

Per the WHO, the global population of individuals aged 60 and above is steadily rising. Projections for 2030 estimate 1.4 billion elderly, with that number expected to reach 2.1 billion by 2050. This demographic shift is viewed from two perspectives: one celebrates the achievement of extended lifespans, recognizing the valuable contributions elders make to society through their wisdom and experience. The other perspective highlights the challenges posed by aging, considering it a significant medical and social issue. The WHO stresses the importance of dismantling age-related biases to prevent discrimination against the elderly and promote healthier attitudes towards aging.

The aging population presents a growing global phenomenon. Approximately half of individuals over 75 experience physical and/or mental impairments, with dementia posing a major challenge to their well-being and that of their caregivers. Aging also affects the perception of facial expressions, hindering emotional communication and potentially leading to social isolation. This underscores the importance of technology in enhancing the quality of life for the elderly, irrespective of cognitive abilities. While technological adoption among older generations remains a challenge, advancements in devices and software have tailored solutions to address their needs.

The rise in life expectancy necessitates increased support, care, and skilled professionals, straining existing health resources. Assistive technologies offer a solution, bridging gaps in healthcare provision and fostering social inclusion in an increasingly digital world.

2. Problem Statement:

The emergence of emotion recognition technology in artificial intelligence has attracted considerable interest, particularly in utilizing facial expressions to extract nuanced emotional data. This not only holds promise for improving human-computer interaction but also advances pattern recognition capabilities. Our objective is to develop an Android application leveraging deep learning models to accurately detect and classify emotions in elderly individuals. The process involves uploading facial images to our server, where a Convolutional Neural Network (CNN) model, trained on a diverse emotion dataset, analyzes the images.

Beyond emotion recognition, the application extends its functionality to assist in eldercare management. It efficiently tracks medication intake, offering timely reminders, and aids in scheduling patient appointments with healthcare providers to ensure comprehensive medical care. Caregivers receive notifications regarding medication schedules and upcoming appointments, enabling proactive support. This integrated system, combining emotion recognition and healthcare management, aims to enhance the overall well-being of elderly individuals and provide valuable assistance to their caregivers. It illustrates the transformative potential of artificial intelligence in addressing essential aspects of healthcare and human interaction.

3. Goals and Anticipated Results

Objectives delineate the aims to be attained, while expected outcomes forecast the projected results. They serve to provide clear direction, guiding endeavors toward desired accomplishments, fostering accountability, and effectively measuring success.

A. Goals

The primary goals of this project are as follows:

- Develop an Android application utilizing deep learning methodologies to recognize facial expressions of elderly individuals.
- Create a system capable of processing medication data for individuals and sending notifications to caregivers regarding medication intake.
- Establish a system to manage patient appointment data and send notifications to caregivers concerning upcoming doctor appointments.
- Assist caregivers in managing elderly individuals by providing real-time updates on patients' mental status and offering pertinent notifications regarding medication intake and appointments.

B. Anticipated Results

Anticipated resultss of this project include:

- Development of a deep learning model utilizing the Keras framework to classify dataset images effectively.

- Implementation of a user-friendly graphical interface to facilitate ease of use for end-users.
- Accurate classification of input facial images into distinct emotion categories.
- Effective management of appointment and medication data, with the system preprocessing individual images to refine the facial emotion dataset.
- Timely provision of notifications to caregivers regarding appointment and medication schedules.

4. System Architecture

System architecture encompasses the process of structuring an architecture for various components, interfaces, and modules of the system, along with providing relevant data essential for implementing these elements effectively. It serves as the fundamental concept underlying the design of any distributed systems. System design entails identifying data sources and entails an intuitive approach to characterizing, developing, and planning a framework to meet the needs and requirements of specific businesses.

A. Data Flow Diagram

Figure 1 commences with a start symbol, indicating the initiation of the image upload process. Subsequently, user credentials are inputted, potentially including a username, password, or other access control measures to ensure only authorized users can upload images to the database. The flowchart then verifies the correctness of the entered credentials. If incorrect, the process may terminate or prompt the user to retry. Upon successful verification, the next step involves uploading appointment data associated with the image, such as the patient's name, date of birth, appointment date, and doctor's name. Finally, the medical image itself is uploaded to the database.

The flowchart does not specify the image format (e.g., DICOM, JPEG), but medical databases typically adhere to standardized formats to ensure compatibility and image integrity.

Depending on the specific database, this step may involve categorizing the image into different classifications based on its content. For instance, the image could be categorized by body part (e.g., X-ray of the chest, MRI of the brain), medical condition (e.g., fracture, tumor), or imaging modality (e.g., CT scan, ultrasound). This categorization, which may be specific to certain databases, could include analyzing the image to detect emotions related to the patient's condition. For example, an algorithm might analyze facial expressions in an ultrasound image to detect fetal distress.

Subsequently, any pertinent medication data associated with the patient or appointment is uploaded to the database. This may encompass medication names, dosages, and administration times. Upon completion of the data upload, the system might generate a notification to inform relevant personnel (e.g., doctors, radiologists) that the image and associated data are now accessible in the database. The process concludes with an end symbol, indicating the successful upload of the medical image and associated data to the database.

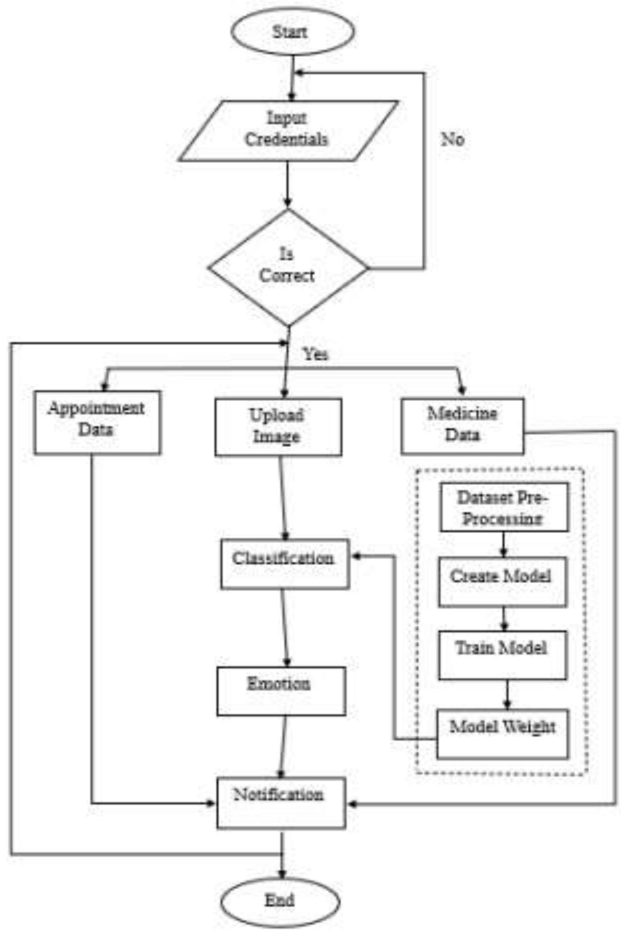

Figure 1: Data Flow Diagram

In essence, this flowchart delineates a standard procedure for uploading medical images to a database, emphasizing secure access, accurate data association, and opportunities for subsequent analysis or notifications. Nonetheless, it's crucial to acknowledge that the particulars and functionalities can vary depending on the specific database and its intended application.

B. System Architecture

The system architecture represents the foundational blueprint and arrangement of a computing system, encompassing its hardware elements, software elements, networks, and their collaborative mechanisms to accomplish predefined functionalities and objectives. It establishes a structured approach for the efficient creation, fusion, and administration of intricate systems. At its core, system architecture focuses on delineating the constituents of the system, defining their roles and connections, and outlining the channels for communication and data interchange among them.

It aims to ensure that the system meets its performance, scalability, reliability, security, and other quality benchmarks. Typically, the design phase commences with a thorough requirements analysis, pinpointing the expectations and constraints of stakeholders. This insight guides the design journey, encompassing tasks such as choosing suitable hardware platforms, determining software frameworks and programming languages, and establishing protocols for inter-component communication

The user will interact with the system via a web application. Each uploaded test image undergoes processing by a deep learning model to predict its class. The deep learning module comprises four primary functions: model creation, training, saving model weights, and classification.

The dataset required for the proposed system is sourced from the internet and augmented to generate additional instances using various techniques such as scaling, zooming, and rotation. A Convolutional Neural Network (CNN) model is constructed to train the system by extracting image features. The deep learning model predicts the user's emotion type from the input image. Additionally, the system offers notifications to elderly individuals concerning medication intake and doctor appointments.

5. Implementation of the System

An essential stage within the system development life cycle involves the effective execution of the new system design. Implementation essentially refers to the transition of the new system design into operational use. The term "implementation" encompasses various interpretations, spanning from the adaptation of a simple application to the complete replacement of a computer system. In this context, implementation denotes the process of transforming a new or updated system design into a functional operational entity.

A. Model Used

The model used in this project is Customized Convolution Neural Network (CNN).

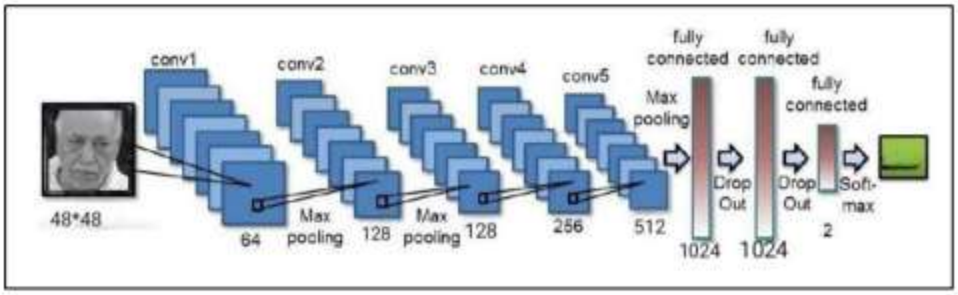

Figure 2: Customized Convolution Neural Network

The architecture of the Figure 2 convolutional neural network (CNN) is meticulously designed for image classification, proficient at transforming 48x48 pixel grayscale input images into meaningful representations to accurately categorize them. Commencing with an input layer, it systematically utilizes convolutional layers (conv1-conv5) to extract features, progressing from basic to intricate representations by progressively increasing the number of filters (64 to 256). Interspersed within the network, max-pooling layers compress spatial dimensions, strengthening robustness by highlighting crucial features while eliminating redundancies. Dropout layers strategically positioned combat overfitting by randomly deactivating neurons during training, thereby improving generalization. Fully connected layers amalgamate high-level features for classification, culminating in a SoftMax layer with two output neurons for binary classification tasks. This architecture, in line with conventional CNN paradigms, combines convolutional and pooling layers for feature enhancement, complemented by fully connected layers for classification. Its flexibility allows for customization to accommodate various task complexities and computational constraints, ensuring effectiveness in discerning intricate patterns within image data.

B. Data Used

All photos have been registered and resized to 48*48 pixels. This dataset contains 35,685 images, 48x48-pixel dimension of faces displaying a range of emotions 7 emotions.

Emotion labels in the dataset are as follows:

0: 4593 images- Angry
1: 705 images- Disgust
2: 5121 images- Fear
3: 8989 images- Happy
4: 6077 images- Sad
5: 4002 images- Surprise
6: 6198 images- Neutral

Figure 3: Dataset

The Face Expression Recognition (FER) dataset contains images representing a range of emotions, including happiness, sadness, disgust, fear, surprise, anger, and neutrality. These datasets play a crucial role in training Convolutional Neural Network (CNN) models to identify human emotions from still images. They cover a variety of characteristics such as gender, ethnicity, and age, which aid in building resilient emotion recognition models. Utilizing CNN architectures, one can analyze these datasets to precisely categorize emotions.

6. Results

In this section, we present the evaluation of the described DL approach. To validate our model, we conducted a series of experiments using the age-expression datasets FACES [24] and Lifespan [25].

The FACES dataset comprises images of 171 individuals displaying six different expressions (anger, disgust, fear, happiness, sadness, and neutrality). The subjects are categorized into three age groups: young (19-31 years old), middle-aged (39-55 years old), and older (69-80 years old). Each subject has two examples of each expression, resulting in a total of 2052 frontal images in the dataset.

The Lifespan dataset consists of faces from individuals of various ethnicities displaying different expressions. The subsets of expressions have the following sizes: 580 for neutrality, 258 for happiness, 78 for surprise, 64 for sadness, 40 for annoyance, 10 for anger, 9 for grumpiness, and 7 for disgust.

For evaluating the performance of the methodology, we only considered facial expressions of older adults, which were pre-processed. As a result, 684 images (57 older adults displaying each of the six expressions twice) from the FACES dataset were used for training and testing, while only 223 neutral faces and 69 happy faces from the Lifes

	# of images						Total
	anger	disgust	fear	happy	sad	neutral	
FACES	114	114	114	114	114	114	**684**
Lifespan				69		223	**292**

Table 1. Two aging datasets (FACES and Lifespan) with the corresponding number of facial expressions used for the evaluation of the proposed methodology

7. Conclusion

The application of deep learning for automatic recognition of facial expressions in elderly individuals demonstrates its potential to significantly alleviate caretaker strain while enhancing the quality of care for seniors. Employing Convolutional Neural Networks (CNNs), the system adeptly manages facial emotion datasets, enabling the extraction of nuanced emotional cues from images of elderly individuals. Prior to processing, the dataset undergoes thorough pre-processing to optimize it for subsequent deep learning model training.

Through training on pre-processed data, this algorithm enhances its accuracy in recognizing facial expressions, furnishing caretakers with real-time insights into the emotional states of the elderly under their supervision. Moreover, the system extends beyond emotion recognition, incorporating functionalities for continuous caretaker support. By incorporating reminders for upcoming medical appointments and medication schedules, the system ensures prompt action and adherence to medication regimens.

This comprehensive approach to elder care management addresses not only the pressing need for emotional support and monitoring but also the broader spectrum of healthcare requirements essential for the well-being of older individuals. By delivering timely notifications and comprehensive assessments of the emotional well-being of the elderly, the proposed system fosters a supportive and nurturing environment. It equips caretakers with the information necessary to anticipate and fulfill the needs of older adults more effectively, ultimately enhancing the quality of care provided.

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