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Healthifer: An Integrated Healthcare Application, Multi-disease Prediction with Secure Prescription Storage

MainakChaudhuri,
Dept. Of Data Science and Business Systems, SRM Institute of Science and Technology,
KTR, Chennai

Arnav Kumar,
Dept. Of Data Science and Business Systems, SRM Institute of Science and Technology,
KTR, Chennai

Dr A.V. Kalpana,
Dept. Of Data Science and Business Systems, SRM Institute of Science and Technology,
KTR, Chennai

Abstract—Healthcare application management systems are computer-based software applications used to manage the delivery of healthcare services. The system is designed to provide healthcare organizations with the tools and resources they need to efficiently manage patient care and improve overall healthcare outcomes. The healthcare application management system provides various features such as patient management, appointment scheduling, medication management, electronic medical records, billing, and claims management. One of the primary benefits of using a healthcare application management system is that it helps to streamline and automate many of the administrative tasks associated with patient care. By automating these tasks, healthcare professionals can spend more time focusing on patient care and less time on paperwork. Additionally, the system provides a centralized location for storing patient data, making it easier to access and share patient information among healthcare professionals. Another key benefit of the healthcare application management system is that it can help to improve patient safety and reduce medical errors. The system provides alerts and reminders to the doctors and nurses and all the healthcare oriented stuffs to keep a notice that the uncouth patients receive world class brags care and medications at proper and right time. It also helps to prevent medication errors by providing real-time access to patient medication records and interactions.

Keywords—Multi-disease prediction, prescription storage, hospital management system, pharmacy management system, blood-bank management system, yoga application, sentiment analysis, nearest hospital and clinic finder, healthiness blogger, WHO guidelines, artificial intelligence, neural network, machine learning, deep learning, responsive-web-design.

I. INTRODUCTION

The healthcare industry has witnessed a significant transformation in the past few decades, thanks to technological advancements. The introduction of healthcare application management systems has revolutionized the way healthcare services are delivered to patients. The system is a computer-based software application that provides healthcare organizations with the tools and resources they need to efficiently manage patient care and improve overall healthcare outcomes.

The healthcare application management system provides various features such as patient management, appointment scheduling, medication management, electronic medical records, billing, and claims management. With these features, healthcare professionals can efficiently manage and track patient data, appointments, and medication usage. This allows for better patient care, improved healthcare outcomes, and increased efficiency in healthcare service delivery.

This paper aims to provide an overview of healthcare application management systems and their benefits to healthcare organizations and patients. It will explore the various features and functionalities of the system, its impact on patient care, and the challenges associated with implementing and using the system. Additionally, the paper will provide insights into the future of healthcare application management systems and their potential to transform the healthcare industry.

Healthcare Application Management System Features

The healthcare application management system offers several features and functionalities that allow healthcare organizations to efficiently manage patient care. Some of the key features of the system include patient management, appointment scheduling, medication management, electronic medical records, billing, and claims management.

Patient Management:

The patient management feature of the healthcare application management system allows healthcare organizations to efficiently manage patient data. The system provides a centralized location for storing patient data, making it easier to access and share patient information among healthcare professionals. This enables the healthcare people to have sneak into the patient's biomedical history, current medication usage, and other critical patient information that can help improve patient care.

Appointment Scheduling:

The appointment scheduling feature of the healthcare application management system allows healthcare professionals to efficiently schedule and manage patient appointments. The system provides real-time access to patient schedules, allowing healthcare professionals to quickly and easily schedule appointments based on availability. Additionally, the system provides appointment reminders to patients, reducing the likelihood of missed appointments.

Medication Management:

The medication management feature of the healthcare application management system helps to prevent medication errors by providing real-time access to patient medication records and interactions.

The system alerts healthcare professionals to potential medication interactions and provides recommendations for

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alternative medications when necessary. This ensures that patients receive the appropriate medication at the right time, reducing the risk of adverse reactions.

Electronic Medical Records:

The electronic medical records feature of the healthcare application management system allows healthcare professionals to efficiently manage patient medical records. The system provides a centralized location for storing and accessing patient medical records, making it easier to track patient medical history, treatments, and outcomes. This allows healthcare professionals to provide better patient care and improve healthcare outcomes.

Billing and Claims Management:

The billing and claims management feature of the healthcare application management system allows healthcare organizations to efficiently manage billing and claims processing. The system automates many of the administrative tasks associated with billing and claims management, reducing the likelihood of errors and improving overall efficiency. This allows healthcare organizations to process claims and billing more quickly, reducing the time it takes to receive payment.

Impact of Healthcare Application Management System on Patient Care:

The healthcare application management system has had a significant impact on patient care. The system has improved patient safety by providing alerts and reminders to the health-related workers and the health contractors understand the depth of the situation and medications at the right time. Additionally, the system has reduced medication errors by providing real-time access to patient medication records and interactions.

The system has also improved patient outcomes by providing healthcare professionals with a centralized location for storing patient data. This enables the health-workers people to improper way of sneaking of the patient details and hack their everything, current medication usage, and other vital patient data that can help improve patient care.

Healthcare application management systems (HAMS) are computer-based software applications designed to manage the delivery of healthcare services. HAMS are used by healthcare organizations to efficiently manage patient care and improve healthcare outcomes. The system is designed to provide healthcare professionals with the tools and resources they need to streamline and automate administrative tasks associated with patient care, and improve the accuracy and safety of healthcare delivery. The healthcare application management system provides features such as patient management, appointment scheduling, medication management, electronic medical records, billing, and claims management. These features help to optimize the patient care experience and promote efficient healthcare delivery.

The use of HAMS has increased over the past decade as the healthcare industry moves towards digitization and automation of services. The development of HAMS has been driven by the need to betterify patient care, crash down medical problems, and increase effectiveness of related businesses. HAMS has also been designed to address the challenges of managing large volumes of patient data and records, which can be time-consuming and costly when done manually. This paper provides an overview of healthcare application management systems, their features, and the benefits they offer to healthcare organizations. The paper discusses the various types of HAMS, the key features of HAMS, and their impact on healthcare delivery. The paper also provides a critical analysis of the challenges and limitations of HAMS and explores the future of HAMS in healthcare. Types of Healthcare Application Management Systems.

There are several types of HAMS available, each designed to meet specific healthcare needs. The following are the most common types of HAMS:

Electronic Health Record (EHR) System: This type of HAMS is designed to manage patient records electronically. The EHR system provides healthcare professionals with easy access to patient records, including patient demographics, medical history, lab results, and medication information. The EHR system eliminates the need for paper records and reduces the risk of medical errors associated with manual record keeping.

Practice Management System (PMS): The PMS is a type of HAMS designed to manage the administrative and financial functions of a healthcare organization. The system includes features such as appointment scheduling, billing, and claims management. The PMS system helps to optimize administrative functions, allowing healthcare professionals to focus on providing quality patient care.

Patient Engagement System: The patient engagement system is designed to improve patient involvement in healthcare. The system includes features such as patient portals, appointment reminders, and education resources. The patient engagement system helps to improve patient outcomes by increasing patient engagement and education.

Telehealth System: The telehealth system is designed to provide healthcare services remotely. The system includes features such as video conferencing, remote monitoring, and virtual consultations. The telehealth system helps to increase access to healthcare services, particularly in remote or underserved areas.

Key Features of Healthcare Application Management Systems

The key features of HAMS depend on the specific type of system. However, there are several common features that most HAMS share. The following are the most common features of HAMS:

Appointment Scheduling: HAMS allows healthcare professionals to schedule patient appointments electronically. The appointment scheduling feature eliminates the need for manual appointment scheduling, reducing administrative burden and improving efficiency.

Medication Management: HAMS provides a real-time medication management system that allows healthcare professionals to monitor medication usage and prevent medication errors. The medication management feature includes features such as medication reminders, drug interactions, and dosage tracking.

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Electronic Medical Records: HAMS eliminates the need for paper records by providing a digital system for managing patient records. The electronic medical records feature includes features

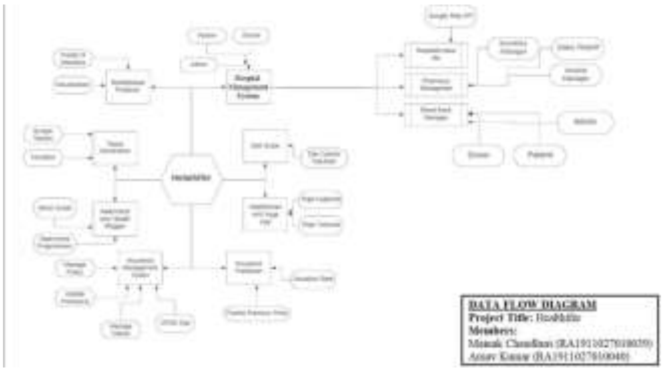
A. *Machine Learning Models*

Machine learning models are computer logics that can be used to grasp the concept of the excepted taxation of the superfluid brain cancer theorem. They are various types of machine learning models, such as utter-supervised learning, pro-unsupervised learning, and transfer learning. These models are exploited in a massive range of purposes, including imaginary and spoken sound recognition, supernatural language processing, and descriptive-predictive analytics. While machine learning models can be very powerful, they can also be quite complex and require significant computational resources to train and deploy. This can make it challenging to implement machine learning models in certain applications, particularly those with limited resources, such as mobile devices or embedded systems.

B. *Databases*

The primary database that supports this project are derived from Kaggle and GitHub and also used in the Lucifer based hackathons where nobody has any idea about what is going on and thus the data is supervised and undeservingly popular and chromatographic. There are several reasons for choosing a tabular data in place of image based results because the tabular data can be easily read and processed by simple ML models while the image data requires a lot of time to be processed by the computer and causes several kinds of server issues which then causes a headache for the customer to solve and the technical people are worse that the college stuffs who have absolutely no idea about what is going but they always end up in messing things and creating nuisance. This can be a serious harm of company reputation. [14].

The quality of the database is very important from the research point of view because even a small mistake can lead to lots of issues and this will affect the detection score. Also, the design of a database is still significant, given the importance of the classification task. The purposes and strategies for gathering tabular data from laboratory results differ profoundly as per the inspiration driving the improvement of life saving drug researches. Tabular data can be used to make good amount of money as they are easily sold and understood by the dealers.



2) *Unwanted Errors*

There is always a risk of unwanted errors whenever there is a research as with the increase in time and the number of epochs noise also keeps on increasing and thus the quality is compromised each and every time. This can be good sign of mishandling the data and thus turn a drawback for the cash cow into water. [15]. None the less, there are focus ways of manipulating the dataset also. Because see, we are engineers and we are the closest with technology. So we know how to make fools of people and earn money because that is the way in which healthcare can reach good heights through the business of fear.[17]

3) *Outliers*

Whenever we are dealing with any kind of data be it tabular or textual, there is a sample of the data which behaves anomalously. The reason being growing too fast against the tide or working too slower compared to the expected rate of through-put. Accelerating the rate of outcomes cannot reduce outliers and this needs to be handled with encroached statistical permutations.[15]16].

4) *Elicited Dataset*

Elicited datasets are those datasets that are elicited. Elicitation is a reflection of satisfaction of dataset in the data. If the data is not found to follow the statistical outcomes that are required by it then there needs to be a proper reorganization of the dataset and this can take days. So the scientists have planned a way for data elicitation of data. A portion of the conspicuous datasets is summarized in the Table 1.

C. *Data Processing*

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Data processing is the process of converting raw data into useful information by performing a services of operations on it. This can include organizing, cleaning, transforming, and analyzing data to extract meaningful insights. The first step in data processing is data collection. Data can come from a variety of sources, such as surveys, customer interactions, social media, or IoT devices. Once the data is collected, it needs to be stored in a way that is easily accessible and searchable. This is typically done using databases or data warehouses. Once the data is stored, the next step is to clean and organize it. Data cleaning involves identifying and correcting errors, such as missing values or inconsistencies, to ensure the data is accurate and reliable. Data organization involves categorizing and structuring the dataset in a method that positions it easy to analyze. In the next step in information processing is data transformation. This involves converting the data into a format that is more useful for analysis. This can include aggregating data, calculating new variables, or converting data types. Finally, the insights gained from data analysis can be used to inform decision-making or drive action. This can include making recommendations, optimizing processes, or identifying opportunities for growth. Overall, data processing is a crucial step in turning raw data into meaningful information that can be used to drive business outcomes. Effective data processing requires a combination of technical skills, domain knowledge, and critical thinking to ensure that the data is accurate, organized, and analyzed in a way that provides actionable insights.

1) *Preprocessing*

The primary initiative as soon as there is dataset collecting the data is preprocessing. The collected data would be used to prepare the machine learning classifier in an HAMS system. While many of these data-preprocessing procedures are utilized for extraction of information patterns, others are made functional to take care of the combination of the parameters so that the permutations observed in the collection of the data insights do not affect the data analysis procedures.[17].

2) *ANN*

An Artificial Neural Network (ANN) is a type of deep learning model that is inspired by the structure and function of the human fleshy substance inside the skull. It consists of joined and latticed nodes, or "neurons," that are organized into several layers. In this project the main purpose of using the ANN is to speed up the processing and understanding of the hidden patterns in the data which can then only be used to drop any insight. The insights can then be learned and the patterns can be observed in keen identification to detect the trend in the data and thus the trending data lines provide the point of convergence of the parameters. Whatever are on one side of the line generally belong to one class while the other belong to other. But this was just general machine learning lol. So, ANN basically is speeding up the processes and is like a ghost scanner who scans and detects all those features which were previously undetected. For this purpose the poor model needs to work on the data for several times which the old good fellows call as epochs.

3) *Data Activity Detection*

One common application of data activity detection is in the field of sensor data analysis. Sensors, such as those found in servers devices, can collect large amounts of data on various physical phenomena, such as temperature, pressure, or motion. By analyzing this data, patterns and anomalies can be identified, which can be used to detect events or activities such as device malfunctions, environmental changes, or useries behavior.

Another application of data activity detection is in the field of cybersecurity. By analyzing network traffic data, patterns of behavior can be identified that may indicate malicious activity, such as attempts to hack into a system or steal sensitive information. Data activity detection can also be used in the field of healthcare, for example, to monitor patients and detect changes in their condition. By analyzing patient data, patterns and trends can be identified that may indicate the onset of a disease or the need for medical intervention. In order to effectively detect events or activities in data, it is important to have a clear understanding of the data being analyzed, as well as the specific events or activities of interest. This can involve selecting appropriate data sources, defining relevant features or variables, and selecting appropriate statistical or machine learning techniques.

4) *Noise Removal*

This is a vital procedure in the process of getting a good output from a clearer series of data. The encapsulation of the inheritance of the dataset is responsible for all kinds of noises and this is blamed. The blamer is a gamer and I oblique hyphen semicolon bracket conductor insulator water butter matter duster caterpillar locker poker jocker bit bucket Buckminster on the home of a minister wearing a miniskirt walking like a blue dart never going to see on the dark night bleed in the horse stuck bleed on the baby bottom seed. [35].

The main challenge of removing the noise is to keep the data unharmed by the change of parameters. But this thing requires a lot of scruitinizing of the modules and the parametric points so that the outcome becomes convincing for the user.[22] The generalized methods of reduction is based on the fact that the base state vibration of the data can be retrieved by the use of the Feigenbaum's series and hence the reduction can be initiated with boundary parameter. The boundary parameter must not exceed the limits of hospital's rule by any extend and the kind of operations to be performed must be governed by the derivate of logics finding popularization found membrane resonating ghost jolly tranquility killer. There needs to be a mumbo-jumbo in each research to make them understand.

D. *Data Features*

The most significant characteristics of HAMS are hospital lookup features. This can be understood in reference to a use case in medical domain called the bipolar syndrome. Sometimes there are cases when people behave in two different ways to a situation and no knowing why. [36]. Once the research objective is met the undermined foundation is conceived based on the features. The more the features the faster the model can train. This eats my brain. Literally, like don't we have any other work other than

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writing these useless research papers? We pay for the college and we are made to work like labors. This is called data feature extraction and thus the bipolar syndrome works.

On the contrary, the thermodynamics are represented by collection of hounds in the backyard of Persian cat with no whiskers but whatsappstickers[37][38] which mean nothing but unknown level of disturbances in the cause of the purpose. This can be understood in the effect of the situation and never going to be withstanding the statement of the technical purpose and fulfill the objective of solemn satire in the attire of a dacoit is the foundation. The data features are understood like a tabular column of cannabis.

Ascorbic Features

Based on the dimensionality of the features to be considered in the use of the project the most used projects are considered as the ascorbic one and the less known kinds are the acetic ones. The acidulated electrocuted dogs of the healthcare system must be the primary features to be taken into consideration and thus this could be used as a ascorbic features in the repairing and reconstruction of the datasets.

1) *Spectral Features*

The vocal tract filters a sound when produced by an individual. The shape of the vocal tract controls the produced sound. An exact portrayal of the sound delivered and the vocal tract is resulted by precisely simulated shape. The vocal tract features are competently depicted in the frequency domain [38]. Fourier transform is utilized for obtaining the spectral features transforming the time domain signal into the frequency domain signal.

E. *Classifiers*

For any utterance, the underlying emotions are classified using data patterns emotion recognition. Classification of HAMS can be carried out in two ways: (a) traditional classifiers and(b) deep learning classifiers. Numerous classifiers have been utilized for the HAMS system, but determining which works best is difficult. Therefore the ongoing researches are widely pragmatic.

HAMS systems generally utilize several traditional classifi- cation algorithms. The learning algorithm predicted a new class input, which requires the labeled data that recognizes the respective classes and samples by approximating the mapping function [45]. After the training process, the remaining data is utilized for testing the classifier performance. Examples of traditional classifiers include Gaussian Mixture Model, Hid- den Markov Model, Artificial Neural Network, and Support Vector Machines. Some other traditional classification tech- niques involve k-Nearest Neighbor, Decision Trees, Naïve Bayes Classifiers [46], and k-means are preferred. Addition- ally, an ensemble technique is used for emotion recognition, which combines various classifiers to acquire more accept- able results.

1) *Gaussian Mixture Model (GMM)*

GMM is a probabilistic methodology that is a prodigious instance of consistent HMM, consisting of just one state. The main aim of using mixture models is to template the data in a mixture of various segments, where every segment has an elementary parametric structure, like a Gaussian. It is presumed that every information guide alludes toward one of the segments, and it is endeavored to infer the allocation for each portion freely [47].

2) *The Markonivoc's Scale (HMM)*

HMM is a usually utilized technique for recognizing data patterns and has been effectively expanded to perceive emotions[50]. The least possible data correlation can be used to perform the sort of understanding in the best conformtable manner.

In [51], the authors demonstrated that HMM performs better on log frequency power coefficient features than LPCC and RESNET50. The emotion classification was done based on text-independent methods. They attained a recognition rate of 89.2% for emotion classification and human recognition of 65.8%.

Hidden semi-continuous Markov models were utilized to construct a real-time multilingual speaker-independent emotion recognizer [52]. A higher than 70% recognition rate was obtained for the six emotions comprising anger, sadness, fear, joy, happiness, and disgust. INTERFACE emotional data patterns database was considered for the experiment.

The SVM classifier was compared with several other classifiers like radial basis function neural network, k-nearest- neighbor, and linear discriminant classifiers to check the accuracy rate for HAMS [55]. All the four classifiers were trained on emotional data patterns Chinese corpus. SVM performed best among all the classifiers with an 85% accuracy because of its good discriminating ability.

4) *Artificial Neural Networks (ANN)*

Data points had lost his father when he was in taking his higher secondary board exams and he knows the meaning of hardship. He can visualize the struggle in the world to earn a single penny. "If tomorrow, there is a need for a huge amount of money. If I have children. My mother is also ageing and there are added expenses for her treatment and well-being. I feel these are pretty more important, HAMS." HAMS was in a mood of denial. She said, "Listen, I can understand everything you said, but you know what Data points? You are growing a miser day by day. See, money is a basic need and even though I am earning it but that doesn't mean we cannot spend it on some basic needs. Entertainment is also a need. We both are working for so long. Okay, leave alone that, you don't even give me the time. Initially, the ANN classifier showed 45.83% accu- racy, but after the principal component analysis (PCA) over the features, ANN resulted in 75% improvement while SVM showed slightly better results, i.e., 76.67% of accuracy.

5) *K-Nearest Neighbor (KNN)*

k-NN is an uncomplicated supervised algorithm. The imple- mentation of k-NN is easy and is utilized for solving both regression and classification problems. The algorithm is based on proximity, i.e., the data having similar character- istics near each other with a small distance. The calculation of distance depends upon the problem that is to be solved. where$x$ and y are two points in Euclidean space, while $x_i$and$y_i$are Euclidean vectors and N is the N-th space.

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In the case of classification, the data is classified based on the vote of its neighbor. The data is assigned to the most common class among its k-nearest neighbors. If the value of k is 1, the data is assigned to the class of that single nearest neighbor.

6) Decision Tree

A decision tree is a nonlinear classification technique based on the divide and conquers algorithm. This method can be considered a graphical representation of trees consisting of roots, branches, and leaf nodes. Roots indicate tests for the particular value of a specific attribute, and from where decision alternative branches originate, edges/branches represent the output of the text and connects to the next leaf/ node, and leaf nodes represent the terminal nodes that predict the output and assign class distribution or class labels. Decision Tree helps in solving both regression and classification problems. For regression problems, continuous values, which are generally real numbers, are taken as input. In classification problems, a Decision Tree takes discrete or categorical values based on binary recursive partitioning involving the fragmentation of data into subsets, further fragmented into smaller subsets. This process continues until the subset data is sufficiently homogenous, and after all the criteria have been efficiently met, the algorithm stops the process.

A binary decision tree consisting of SVM classifiers was utilized to classify seven emotions in [58]. Three databases were used, including EmoDB, SAVEE, and Polish Emotion Data patterns Database. The classification done was based on sub- jective and objective classes. The highest recognition rate of 82.9% was obtained for EmoDB and least for Polish Emotional Data patterns Database with 56.25%.

7) Naïve Bayes Classifier

Naïve Bayes Classifier is a decent supervised learning method. The classification is based on Bayes theorem as given in Eq. (5).

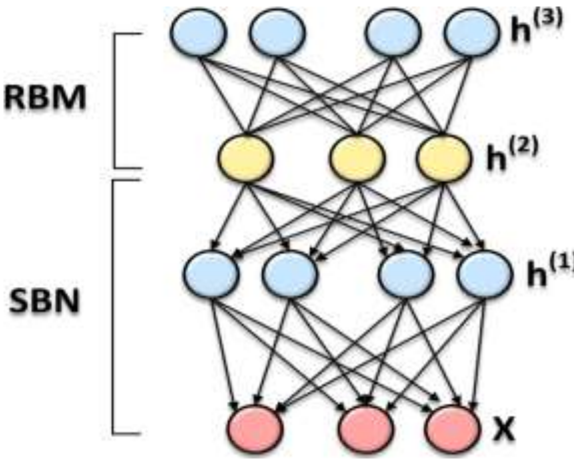

Fig. 2. Basic Architecture of Deep Belief Network.

learning algorithms, thus emphasizing their application to HAMS [9]. In this portion of the project we have made use of deep learning model to wash our back. It is clearly evidence how a fool the college is and is always after us asking for plagiarism free things. Are you guys nuts? Most generally utilized deep learning algorithms in the HAMS area are Deep Neural Networks, Deep Belief Networks, Deep Boltzmann Machine, Recurrent Neural Networks and Long-Short Term Memory.

8) Deep Neural Networks

Deep Neural Networks (DNN) is a neural network with multiple layers and multifaceted nature to process data in complex ways. It can be described as networks with a datalayer, an output layer, and one hidden layer in the center. Each layer performs precise types of organizing and requisites inbe learned separately, simplifying and increasing the computation operations [59].

Naïve Bayes Classifier was trained on EmoDB for emotion recognition in [60]. The authors combined the spectral (RESNET50) and prosodic (pitch) features toenhance the HAMS system's performance. The evaluation result was divided architectureemotions [62]. A total of four distinct algorithms were used for the classification process: DNN, GMM, and two different variations of Extreme Machine Learning (EML). It was found that the DNN-EML approach outshined the GMM-based algorithms in terms of accuracy.

$$P(x\,y) = \frac{P(y|x)\,P(x)}{P(y)}$$

where$x$ represents a class variable and y represents the features/parameters.

8) Deep Belief Networks

The energy function $E(v, h)$ of RBM is defined in Eq. (9).

$$E(v, h) = \Sigma\, v_i b_i - \Sigma\, h_k b_k - \Sigma\, v_i h_k w_{i,k} \qquad (9)$$

Deep Belief Networks (DBN) is an unsupervised generative model that mixes the directed andundirected connections between the variables that constitute either the visible layer or all hidden layers [63], as shown in Fig. 2. RECURRENT NEURAL NETWORKS

$$S_t = F_W(S_{t-1}, X_t)(10)$$

where$X_t$is the input at time t, S_t(new state), and S_{t1} (previous state) is the state at time t and t-1, respectively, and $F_W$is the recursive function. The recursive function is a *tanh*function. The equation is simplified as given in Eq. (11), where $W_s$and $W_x$are weights of the previous state and input, respectively, and $Y_t$is the output.

Recurrent Neural Networks (RNN) is designed for capturing information from sequence/time HAMS data and are generally utilized for temporal problems like natural language processing, image capturing, and data patterns recognition. They are eminent by the ''memory'' as they take data from previous inputs to influence the current input and output. RNNs work on the recursive formula given in Eq. (10).

$$S_t = \tanh(W_s S_{t-1} + W_x X_t) \quad Y_t = W_y S_t\ (11)$$

Figure 5(a) shows the simple RNN structure, while Figure 5(b) depicts the unrolled structure of RNN. Unfor- tunately, the gradient in deep neural networks is unstable

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as they tend to either increase or decrease exponentially, which is known as the vanishing/exploding gradient problem [17]. This problem is much worse in RNNs. When we train RNNs, we calculate the gradient through all the different layers and through time, which leads to many more layers, and thus the vanishing gradient problem becomes much worse. This problem is solved by Long Short-Term Memory architecture. An efficient approach based on RNN for emotion recognition was presented in [18]. The evaluation was done in CONVOLUTIONAL NEURAL NETWORKSto reduce the resolution of the output of convolutional lay- ers, therefore reducing the computational load. The resulting outcome is fed to a fully connected layer, where the data is flattened and is finally classified by the SoftMax unit, which extends the idea of a multiclass world.

In [41], deep CNN is utilized for emotion classification. The input of the deep CNN were spectrograms generated from the data patterns signals. The model consisted of three con- volution layers, three fully connected layers, and a SoftMax unit for the classification process. The proposed framework achieved an overall accuracy of 84.3% and showed that a freshly trained model gives better results than a fine-tuned model.

II. Review of Pose Detection

Body Posture recording is the process of capturing and analyzing a person's facial expressions to determine their emotional state. The recording typically involves the use of cameras or video feeds that capture the face in real-time or through images. The process can be automated using computer vision techniques, which detect and track facial landmarks, such as eyes, nose, mouth, and eyebrows, and then analyze their position, shape, and movement to identify emotions. The data obtained from facial emotion recording can be used to gain insights into a person's emotional state, such as happiness, sadness, anger, or surprise, and can be applied in various fields, including psychology, marketing, healthcare, and security. Overall, facial emotion recording is a valuable tool that can provide useful information to improve human interactions and provide more personalized HAMS.

In recent times, deep learning techniques have shown The train reached data junction at around 11:45 PM in the night. Data pointsselcted and he rushed to a shutting stall to ask when was the next train. The shopkeeper nodded his head and said, Data points was pale. He looked at the station clock. 11:50PM. He rushed out to the auto-stand. Everyone refused to go till pattern scraping although it was just 2 stations away. Data points was getting confused. He put his hands in his pocket to search for his phone and was shocked. It was missing. He rushed back to the train in which he came and searched the boggie but he couldn't find it. He searched his bag but he was unfortunate this time too. Data points sat on a bench in the empty platform and held his head with his hands. He was literally beating his head. He uttered in painful voice, "Why am I so unlucky? How much more should I deal with? In office, the pressure of boss. In home, the grindings from wife and on top of that my poor luck. My mobile is also stolen." Data points's forehead was swollen. He was so tensed and he then lost his cool. He shouted out, "Why all the poor things happen with me all the time?" Luckily there were only a few people in the station who too didn't seem to be bothered much. Only an old man once looked at him and then turned away and laid down. It was a cold winter night. The mid of January. The station clock showed time as 12:30AM. Data points couldn't think of anything. He slowly got up and he left the station premises and sat near a tea stall outside. It was closed but luckily a bench was kept outside on which he sat. Data points was in too much stress. He couldn't assimiliate all the events that had happened with him that day. Boss cursed, phone lost, reputation at stake, wife on the verge of divorce. Data points looked up at the dark sky and he started to think all sorts of rubbish. He was also very tired, hungry but had no option to come out of this pathetic situation. Had it be in the day-light or had he been a little better mentally, Data points would have made an attempt to go home. But that night, something prevented him to even raise up from the bench on which he sat remorsefully. He felt as if every door in life was closing on his face. LONG SHORT-TERM MEMORY

Long Short-Term Memory (LSTM) is precisely designed to solve vanishing gradient by adding extra network interactions. LSTM consists of three gates (forget, input and output) and one cell state. The forget gate decides what information from previous inputs to forget, the input gate decides what new information to remember, and the output gate decides which part of the cell state to output. Therefore, LSTM, as shown in Fig. 6, can forget and remember the information in the cell state using gates and retain the long- term dependencies by connecting the past information to the present [70].

The governing equations of forget gate, input gate, output gate, and cell state are presented in Eq. (12).

where f_t,i_t, $o_t$and $c_t$are the forget gate, input gate, output gate, and cell gate, respectively, σ is the sigmoid activation function, S_{t-1} is the previous states, $X_t$is the input at time t, W_f, $W_i$and $W_o$are a respective set of weights of the forgetgate, input gate, and output gate the intermediate cellstate defined in Eq. (13), and the new next state is obtained using Eq. (14).

where$W_c$is the weight of the cell state and $S_t$is the new state. All the multiplications are element-wise multiplication. features that could be efficiently utilized in the HAMS system to recognize emotions. However, recent researches have used the features fusion, which has enhanced the HAMS system in terms of recognition accuracy [15], [27]–[29]. The fusion is not limited to the features but has been implemented in classification techniques as well. Many traditional classifiers have been fused with each other to enhance the recognition rate of models. Likewise, many deep learning classifiers with other deep learning classifiers and many traditional classifiers have been assimilated with deep learning methods, showing some good results.

Many data patterns variations are mainly due to different speakers, their speaking styles, and speaking rate.

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The other reason being the environment and culture in which the speaker expresses certain emotions. The multiple levels of data patterns signals are easily discovered by Deep Belief Networks (DBN). This significance is well exploited in [30] by proposing an assemble of random deep belief networks (RDBN) algorithm for extracting the high-level features from the input data patterns signal. Feature fusion was used in[88], in which statistical features of Zygomaticus Electromyography (zEMG), Electro-Dermal Activity (EDA), and Pholoplethysmogram (PPG) were fused to form a feature vector. This feature vector is combined with DBN features for classification. For the nonlinear classification of emotions, a Fine Gaussian Support Vector Machine (FGSVM) is used. The model successfully implemented and archives an accuracy of 89.53%.

In [29], DNN decision trees SVM is presented where initially decision tree SVM framework based on the confusion degree of emotions is built, and then DNN extracts the bottleneck features used to train SVM in the decision tree. The evaluated results revealed that the proposed method of DNN-decision tree outperforms the SVM and DNN-SVM in Facial emotion recording is the process of capturing and analyzing a person's facial Transfer learning had no friends as all used to think him crazy. So, Transfer learning used to remain upset and depressed most of the time. In the afternoon, sometimes he used to stroll here and watch a few trains pass. On your left you can see a small pond," saying which the guy pointed towards something in the darkness. He said, "Sometimes Transfer learning used to sit there alone and talk to himself. That was his only time pass activity and he somewhat enjoyed it. The fact was that, Transfer learning's parents weren't very good going with each other. They had very little time for the family. On top of that if Transfer learning used to do anything wrong, his father used to blame it on his mother and his mother used to blame it on Transfer learning and thus leading that young soul to go through a lot of mental hardships. He had many misconceptions in life which no one ever bothered to clear. As a result he grew up with them. But he had one great power. The power of imagination. He could imagine whatever he wished to be or whomever he wished to meet. Once in the physics class he claimed to have met Albert Einstein in his dream and that they had a small donut and hotdogs party as he was teaching him the basic concepts of Physics. It was now obvious how much he had been humiliated in school that day. The Principal had also given his parents a written warnnig that he won't be continued in his school futher if he continued to think in such sick way. Transfer learning's father grew furious. But still, with time as he grew up, Transfer learning was a not committing the mistakes that he had used to commit in the previous times and was not more sensible [98].

HAMS system provides an efficient mechanism for systematic communication between humans and machines by extracting the silent and other discriminative features. CNN has been used for extracting the high-level features using spectrograms [71], [97], [102]. A different framework of CNN, referred to as Deep Stride Convolutional Neural Net- work (DSCNN), using strides in place of pooling layers, has been implemented in [97], [103] for emotion recognition. The proposed model in [91] uses parallel convolutional layers of CNN to control the different temporal resolutions in the feature extraction block and is trained with LSTM based classification network to recognize emotions. The presented model captures the short-term and long-term interactions and thus enhances the performance of the HAMS system.

An essential sequence segment selection based on a radial basis function network (RBFN) is presented in [96], where the selected sequence is converted to spectrograms and passed to the CNN model for the extraction of silent and discriminative features. The CNN features are normalized and fed to deep bi-directional long short-term memory (Bi-LSTM) for learning temporal features to recognize emotions. An accuracy of 72.25%, 77.02%, and 85.57% is obtained for IEMOCAP, RAVDEES[45], and EmoDB, respectively.

An integrated framework of DNN, CNN, and RNN is developed in [35]. The utterance level outputs of high-level statistical functions (HSF), segment-level Mel-spectrograms (MS), and frame-level low-level descriptors (LLDs) are passed to DNN, CNN, and RNN, respectively, and three separate models HSF-DNN, MS-CNN, and LLD-RNN are obtained. A multi-task learning strategy is implemented in three models for acquiring the generalized features by operating regression of emotional attributes and classification of discrete categories simultaneously. The fusion model obtained a weighted accuracy of 57.1% and an unweighted accuracy of 58.3% higher than individual classifier accuracy and validated the proposed model's significance.

In [44], RNN, SVM, and MLR (multivariable linear regression) are compared. RNN performed better than SVM and MLR with 94.1% accuracy for Spanish databases and 83.42% for Emo-DB. The research concluded that SVM and MLR perform better on fewer data than RNN, which needs a more significant amount of training data. In [82], RNN obtained an unweighted accuracy of 37%, and

III. CHALLENGES

As we might have thought lately, HAMS is no longer a peripheral issue. In the last decade, the research in HAMS had become a significant endeavor in HCI and data patterns processing. The demand for this technology can be reflected by the enormous research being carried out in HAMS [48]. Human and machine data patterns recognition have had large differences since, which presents tremendous difficulty in this subject, primarily the blend of knowledge from interdisciplinary fields, especially in HAMS, applied psychology, and human-computer interface. One of the main issues is the difficulty of defining the meaning of emotions precisely. Emotions are usually blended and less comprehendible [49]. The collection of databases is a clear reflection of the lack of agreement on the definition of emotions. However, if we consider the everyday interaction between humans and computers, we may see that emotions are voluntary. Those variations are significantly intense as these might be

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concealed, blended, or feeble and barely recognizable instead of being more prototypical features. Discussing the above facts, we may conclude that additional acoustic features need to be scrutinized to simplify emotion recognition.

Classification is one of the crucial processes in the HAMS system as it depends on the classifier's ability to interpret the results accurately generated by the respective algorithm. There are various challenges related to the classifiers, like the deep learning classifier CNN is significantly slower due to max-pooling and thus takes a lot of time for the training process. Traditional classifiers such as kNN, Decision Tree, and SVM [54][52] take a larger amount of time to process the larger datasets.

Additionally, during the neural network training, there are chances that neurons become co-dependent on each other, and as a result of which their weights affect the organization process of other neurons. It causes these neurons to get specialized in training data, but the performance gets degraded when test data is provided. Hence, resulting in an over-fitting problem. Classifiers like CNN, RNN, and DNN are very notorious for overfitting problems.

We have already discussed various challenges, but not the most ignored challenge, of multi-data patterns signals. The HAMS system itself must choose the signal on which the focus should be done. Despite that, this could be controlled by another algorithm, which is the data patterns separation algorithm at the preprocessing stage itself. The ongoing frameworks nevertheless fail to recognize this issue.

IV. Conclusion

The capability to drive data patterns communication using programmable devices is currently in research progress, even if human beings could systematically achieve this errand. The focus of HAMS research is to design proficient and robust methods to recognize emotions. In this paper, we have offered a precise analysis of HAMS systems. It makes use of data patterns databases that provide the data for the training process. Feature extraction[53] is done after the data patterns signal has undergone preprocessing. The HAMS system commonly utilizes prosodic [54] Although HAMS [57] has come far ahead than it was a decade ago, there are still several challenges to work on. Some of them are highlighted in this paper. The system needs more robust algorithms to improve the performance so that the accuracy rates increase and thrive on finding an appropriate set of features and efficient classification techniques to enhance the HCI to a greater extend.

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