Qianqian Hu[1*]

Heguang Wang[2]

Bing Wang[3]

Xiaotang Cui[4]

Modeling and Sentiment Analysis of Social Relationships in Elderly Smart Homes Based on Graph Neural Networks

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Abstract: - With the expansion of Speech Emotion Recognition in the consumer domain, several devices, particularly those designed for managing smart home personal assistants for the elderly, have been widely available on the market. The increasing processing power and connection, together with the growing need to facilitate longer residency through technological interventions, highlight the potential benefits of smart home assistants. Enabling these assistants to recognize human emotions would greatly improve user-assistant communication, allowing the assistant to deliver more constructive and customized feedback to the user. In this research work, Modeling and Sentiment Analysis of Social Relationships in Elderly Smart Homes Based on Graph Neural Networks(SASR-MBHNN-BBOA) is proposed. In this the input data are collected from Social Recommendation Dataset. Then, the input data are pre-processed using Inverse Optimal Safety Filters (IOSF) for cleaning the data and removing the background noise. Then the pre-processed data are given to Memristive Bi-neuron Hopfield Neural Network (MBHNN) for predicting the sentiments like positive, negative and neutral. In general, MBHNN doesn't express some adoption of optimization approaches for determining optimal parameters to predicting the sentiments accurately. Hence BBOA is proposed to optimize MBHNN classifier which precisely predicts the sentiments in elderly smart home. The proposed SASR-MBHNN-BBOA method is implemented in Python, and it assessed with numerous performance metrics like accuracy, precision, recall, F1-score, ROC. The results show SASR-MBHNN-BBOA attains 20.8%, 19.5%, and 29.6% higher Accuracy, 28.8%, 22.5%, and 32.6% higher Precision, 15.5%, 27.4%, and 18.2% higher Recall are analysed with existing methods such as, Emotional speech analysis in real time for smart home assistants.(SASR-CNN-SHA), Machine Learning to Investigate Elderly Care Requirements in China via the Lens of Family Caregivers (SASR-ML-IECR),Identifying User Emotions via Audio Conversations with Smart Assistants (SASR-DNN-EASA) methods respectively.

Keywords: Balanced Butterfly Optimization Algorithm, Elderly people, Inverse Optimal Safety Filters, Memristive Bi-neuron Hopfield Neural Network and Social Recommendation Dataset, sentiment analysis, smart home.

I. INTRODUCTION

Picard introduced Speech Emotion Recognition (SER) in 1997, and it has received a lot of attention since then. Language is primarily constructed through speech, which plays a critical role in conveying not just significant semantic information also rich emotional nuances [1, 2]. Goal of SER is to detect a user's emotional states through their speech, promoting harmonic communication among humans and machines, such as the smart home assistants discussed in this paper. Emotion is a complicated state caused by internal or external stimuli that includes physiological reactions, subjective experiences, and exterior activities [3, 4]. Positive emotions correspond to consumers' demands, whilst negative emotions arise from distress or unpleasant experiences. Research into emotion detection for consumer devices began in 2006, release of early music recommender systems, facial expression recognition for personal cameras at 2010 [5, 6]. Consumer market saw the introduction of emotion recognition systems in 2011, which used databases and eventually incorporated biofeedback. Beyond music recommender systems, there are exciting applications such as emotion-aware lighting and service robots [7, 8]. Recent study stresses seamless human-device interaction, which leads to longer, safer, and better living using smart consumer home gadgets. Common feature extraction techniques in speech analysis, according to Venkataramanan and Rajamohan, comprise Log-Mel spectrogram, Human Factor Cepstral Coefficients, Mel scale cepstral analysis, Mel Frequency Cepstral Coefficients, Short Term Fourier Transforms [9, 10]. Such study focuses on developing appropriate technologies, computationally effectual processes that will allow smart home supporters to forecast user emotions and provide more targeted replies to questions and home occurrences [11, 12]. Using an Independent Component Analysis (ICA) approach, the primary audio components are identified and extracted, with Mel Frequency Cepstral Coefficients (MFCCs) functioning as essential prediction coefficients, among other extraction strategies [13, 14].Common feature

[1*]Teaching Assistant, College of Art and Design, Zhengzhou University of Light Industry, Zhengzhou, Henan, China, 450000

[1*]Email: qianqianhuphd@gmail.com

[2]Lecturer, College of Cultural Heritage and Art Design, Zhengzhou University of Technology, Zhengzhou, Henan, China, 450000

[3]Lecturer, Rehabilitation Engineering College, Beijing Vocational College of Social Management (Training Center of the Ministry of Civil Affairs), Beijing, China, 102600

[4]Lecturer, College of Art and Design, Zhengzhou University of Light Industry, Zhengzhou, Henan, China, 450000

extraction techniques in speech analysis, according to Venkataramanan and Rajamohan, comprise Log-Mel spectrogram, Human Factor Cepstral Coefficients, Mel scale cepstral analysis, Mel Frequency Cepstral Coefficients, Short Term Fourier Transforms [15, 16]. Such study focuses on developing appropriate technologies, computationally effectual algorithms that will allow smart home supporters to forecast user emotions and provide more targeted replies to questions and home occurrences [17, 18]. Using an Independent Component Analysis (ICA) approach, the primary audio components are identified and extracted, with Mel Frequency Cepstral Coefficients (MFCCs) functioning as essential prediction coefficients, among other extraction strategies [19, 20].

A. Problem statement with motivation

Addressing the present research gap in modeling and sentiment analysis of social ties in senior smart homes necessitates a focused and specialized strategy. The subtle emotional dynamics and communication patterns of elderly inhabitants in smart home systems are not fully understood. The key difficulty of constructing a complete and effective sentiment analysis model for this specific setting must be addressed. Key aspects, such as senior people's different emotional states, preferences, and communication styles, must be addressed for the successful adoption of assistive and supportive technologies in elderly smart homes. Formulating a concise issue statement is critical for directing research efforts targeted at improving the social and emotional well-being of older inhabitants using modern smart home technology.

The goal is to investigate emotional states in speech, propose deep learning model that balances performance and complexity for use in Consumer Electronics home devices. The goal is also to give practical live demonstration of investigation findings. The study describes a complete approach to human speech-based emotion analysis that employs deep learning to comprehend and categorize the emotions given by human speech.

Major contributions of this manuscript arranged as below:

- This paper examines senior care demands in China through eyes of direct caregivers by extracting texts from registered users discussing elderly care.
- It uses topic modeling and sentiment analysis to examine published materials.
- Building on text mining discoveries, proposes solutions for improving quality of aged care services.
- The BBOA provide comprehensive perspective that will help todevelop design of China's aged care service scheme.

Remaining manuscript is organized as below: part 2 describes literature review, part 3 depicts proposed method, part 4 exhibits the outcomes with discussions, and part 5 concludes this manuscript.

II. LITERATURE REVIEW

Several investigation works presented in literatures were based on Modeling and Sentiment Analysis of Social Relationships in Elderly Smart Homes; few of them were reviewed here,

Chatterjee, et.al [21] have presented the real-time speech emotion analysis for SHA. This paper gives a complete method for analyzing emotions through human speech. The study employs a 1-D CNN to learn, categorize emotions in human speech. Findings show that 1-D CNN classification methods utilized in speaker-independent studies were highly effective at automatically predicting emotions. It provides high Accuracy, and it provides low Precision.

Wang, and Luo, [22] have presented, the Needs of Elderly Care in China from Family Caregivers Perspective by ML Methods. Here, investigates necessities of old people in China by analyzing social media posts about senior care from perspective of caregivers. Using a ML method, The LDA model is used to extract topics and phrases from the text, making it easier to analyse and categorize into important themes around elderly care. The report then recommends tactics based on the data mining results. It provides high Precision, and it provides low Recall.

Guha, [23] have presented to Detecting User Emotions from Audio Conversations with the Smart Assistants. Here, aims to add to current body of knowledge on emotion recognition using voice commands in smart home applications. Initially, I chose two freely available audio chat datasets to determine the best categorization system for my application. After doing a comparison analysis, I discovered that the Tree-based Pipeline Optimization Tool (TPOT) approach outperforms other machine learning algorithms in properly recognizing emotion from audio. It provides high Recall, and it provides low F1-score.

Alnuaim, et.al [24] have presented the human-computer interaction for recognizing speech emotions utilizing multilayer perceptron classifier. Here, aims to use artificial intelligence algorithms to distinguish emotions in human voice. The availability of data is critical to artificial intelligence projects. This study used Ryerson Audio-Visual Database of Emotional Speech and Song open-source dataset. The RAVDESS collection comprises more than 2000 recordings, comprising talks, songs delivered by 24 actors. The data were gathered to reflect the eight distinct moods portrayed by actors. It provides highF1-score, and it provides low ROC.

Alqahtani, et.al [25] have presented the Smart homes and families to enable sustainable societies: Here, introduces the approach for data-driven parameter detection, uses to conduct first detailed and relatively inclusive investigation of families, homes landscape from both academic and popular viewpoints. This analysis was based on a large dataset that includes over 100,000 scientific papers, nearly million tweets. It provides high recall and it provides low precision

Thakur, and Han, [26] have presented framework for intellectual affect aware smart home environment for elderly people. Here, presents a foundation for intellectual affect aware environment intended for senior people. Before appealing in some activity inside smart home environment, framework assesses affective components of interactions, forecasts possible user experience. This predictive feature attempts to improve user experience, making intelligent systems more supportive and adaptive. It provides high Roc, and it provides low Accuracy.

Sánchez-Franco, et.al [27] has presented utilizing structural topic modelling to forecast users' sentiment to intelligent personal agents. Here, a theoretical framework based on technological acceptance methods, the Uses with Gratification Theory. The empirical methodology entails a thorough examination of natural with non-structured narratives related to Amazon's Echo, Google Home. To detect critical aspects has a differential impact on the evaluation of Intelligent Personal Assistants (IPA). It provides high accuracy and it provides low F1-score.

III. PROPOSED METHOD

In this section, SASR-MBHNN-BBOA is discussed. The block diagram of proposed SASR-MBHNN-BBOA shown in Figure 1. The dataset, pre-processing, classification, optimization are processes that make up this procedure. Thus, full description of all stage is given below,

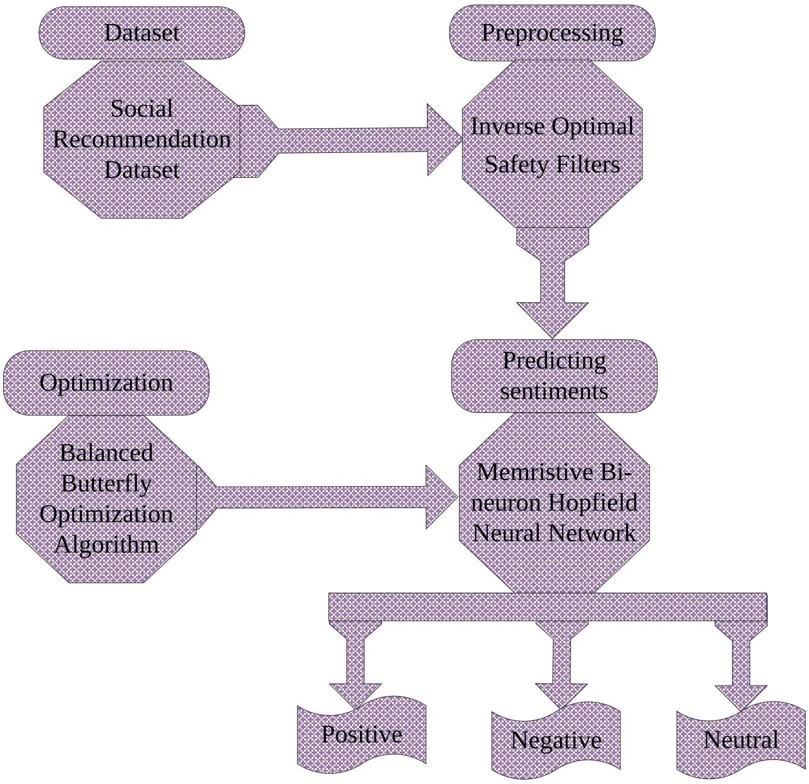

Figure 1: Block Diagram of SASR-MBHNN-BBOA for Sentiment Prediction

A. Elderly People and Smart Homes

Smart homes are residential spaces equipped with advanced automation systems that enhance security, convenience, energy efficiency, and comfort. They utilize internet-connected devices and systems that can be remotely controlled and monitored. For elderly people, smart homes offer several benefits:

1) Benefits of Smart Homes for the Elderly

Safety and Security:

Surveillance cameras, motion detectors, and smart locks are among the devices in smart home systems that give real-time monitoring and alarms. This improves the safety of the elderly, who are more vulnerable to accidents and incursions.

Health Monitoring:

Smart watches, fitness trackers, and medical alert systems can track vital signs and detect falls. They can notify caregivers or medical professionals in case of an emergency.

Convenience:

Automating household duties such as lighting, climate control, and kitchen appliances ease the physical burden on the elderly. Voice-activated assistants like Amazon Alexa and Google Home can help with medication and appointment reminders.

Social Connection:

Smart home technologies allow for improved connectivity with family members via video conversations and social media, minimizing feelings of loneliness.

B. Sentiment Analysis

Sentiment analysis, often known as opinion mining, is a technology that uses natural language processing (NLP) and machine learning to recognize and extract subjective information from text data. It seeks to identify the attitude, feelings, or opinions expressed in a piece of literature. Sentiment analysis has many applications:

1) Integrating Sentiment Analysis with Smart Homes for the Elderly

Monitoring Well-being:

Sentiment analysis can be used on text and speech data acquired from interactions with smart home devices. This can be useful in determining the emotional status of elderly residents.

Customizing Care:

Based on sentiment analysis, smart home devices can alter the environment (lighting, music, and temperature) to boost the elderly's mood and well-being.

Alerting Caregivers:

If the system detects unfavourable sentiment patterns (such as indicators of despair, frustration, or loneliness), it can notify family members or caregivers to provide timely assistance.

Enhancing Communication:

Sentiment analysis can help the elderly communicate more empathetically and effectively with their virtual assistants or robots, making encounters feel more natural and supportive.

C. Data acquisition

The input data is gathered from social recommendation dataset [28]. In 1997, an early social recommender system developed, setting the path for the rapid advancement of this technology. The widespread usage of social media makes social information at unparalleled rate, as evidenced by Facebook's 35,000,000,000 online friendships, Twitter's most popular user with 37,974,138 followers. This spike in social media popularity has hastened improvement of social recommender schemes. This section will define social recommendations, compare opportunities to traditional systems, categorize, review existing schemes, and summarize major results from real experiences with social recommender systems.

D. Pre-processing using Inverse Optimal Safety Filters (IOSF)

In this section, Pre-processing usingIOSF [29] is discussed for cleaning the data and removing the background noise. The fundamental goal of IOSF is to improve control system safety by proactively identifying and mitigating potential risks. It permits the creation of safety filters that can be applied to control inputs to prevent unsafe states or actions. IOSF demonstrates the ability to adapt to ever-changing system dynamics by continuously updating safety filters based on real-time data and system input. Typical issue of safety maintenance is simple. IOSF improve the desired data while reducing the noise component by first simulating the noise properties. The filter is then built to inversely reflect these features, successfully filtering out background noise while keeping the principal audio stream intact. This method is most effective in surroundings with a stable and properly modelled noise profile, resulting in clear and high-quality audio output. By emphasizing inverse features, the filter dynamically adjusts to changing noise levels, providing a reliable solution for noise reduction in applications such as telecommunications, audio recording, and hearing aids.The IOSF has cleaned the data and removed the background noise in equation (1),

$$u = u_o + \beta \bar{u} QP \tag{1}$$

Where, (u) parameter estimator, $(\bar{u})$ denotes as passivity of a method, (u_o) is a normal design, (β) denotes as terminal penalty. By minimizing non-safety measures, safety filter maximizes estimator's safety. This approach entailed modeling the noise characteristics and developing a filter to inversely replicate these features, preserving the required signal while eliminating undesired noise. Finally IOSF has cleaned the data and removed the background voice. Then the pre-processed data are given to MBHNN.

E. Predicting Sentiments using Memristive Bi-neuron Hopfield Neural Network (MBHNN)

In this session predicting Sentiments using MBHNN [30] is discussed. The MBHNN has predicting the sentiments like positive, negative and neutral for elderly smart home. The MBHNN simplifies sentiment prediction tasks, allowing for faster and more efficient calculations. Its economical architecture, along with Memristive properties, enables real-time sentiment prediction, making it ideal for applications requiring quick insights into shifting feelings. The MBHNN is designed to efficiently process and store information by simulating the synaptic connections seen in the human brain. This sophisticated neural network model can recognize complex patterns in sentiment data and forecast them with high accuracy. The use of memristors increases network speed and energy efficiency, making it perfect for real-time sentiment analysis in applications including social media monitoring, customer feedback evaluation, and market research. This technique not only enhances predictive capabilities, but it also provides a more scalable and long-term solution for sentiment analysis.Here, the MBHNN predicted the sentiments in elderly smart homes in equation (2).

$$\eta_2 = -\frac{5}{3}\left[\eta_1 - (w_{11} + 0.72)\tanh(\lambda\eta_1) - k(1 - 4|\eta_1|)\eta_1\right] \tag{2}$$

Where, (η_1, η_2) are the two solutions, (k) is the argument, each equilibrium point trajectories are symmetric, complex stabilities found in MBHNN method, it has more exactly, implying occurrence of complex kinetics in MBHNN method. Finally the MBHNN has predictedthe sentiments like positive, negative and neutral. Due to its convenience, pertinence, AI-depend optimization approach is taken into account in MBHNN classifier. The BBOA is employed to enhance MBHNN optimum parameters (W, η_2). The BBOA is employed for turning weight, bias parameter of MBHNN.

F. Optimization Using Balanced Butterfly Optimization Algorithm (BBOA)

The weight parameters (W, η_2) of proposed MBHNN are optimized using the proposed BBOA [31] is discussed. The efficiency of the Balanced Butterfly Optimization Algorithm is underscored by several key advantages. The algorithm's quick convergence speed accelerates solution finding, making it particularly useful in time-sensitive situations. Its versatility to a variety of issue types, combined with low computational cost and little parameter adjustment requirements, improves both accessibility and usability. Furthermore, the absence of a transfer parameter during the transition from the exploration phase to the exploitation phase directly influences the algorithm's performance. The initiation of involves the initialization step.

1) Stepwise process of BBOA

Here, stepwise process is defined to get ideal value of MBHNN based on BBOA. Initially, BBOA makes the equally distributing populace to optimize parameter MBHNN. Ideal solution promoted using BBOA algorithm, linked flowchart given Figure 2.

Step 1:Initialization

The BBOA, a nature-inspired optimization technique, is initiated by defining the initial placements of its search agents, known as butterflies, within the solution space. The precise initialization equation varies based on the algorithm's implementation or version.

Step 2:Random generation

Input parameters generated at random after initialization. Best fitness value selection is depending upon their explicit hyper parameter condition.

Step 3:Fitness Function

The result comes from initialized assessments and the random response. Then the fitness is calculated by the equation (3)

$$FitnessFunction = Optimizing\ (W, \eta_2) \tag{3}$$

Step4:Exploration Phase

To speed up convergence, the value must be decreased more quickly. The later phases of the search process, smaller number indicates a shorter search step size, a population concentrated in smaller search zone that improves local exploration. However, this results in low population diversity. To avoid trapping the population in a local optimum, reduce the value gradually,

Step 5: Exploitation Phase for optimizing (W, η_2)

Balancing the capabilities of the exploitation phase is critical. To attain this equilibrium, global best solution with two randomly selected solutions are presented into exploitation phase separately. Specifically, during global search phase, an individual improves position by learning from global best solution among present population. This strategy tries to speed up convergence while also improving algorithm's exploitation ability. This is given in equation (4)

$$W(\eta_2) = \frac{w_{\min}}{1 + \left(\frac{w_{\min}}{w_{\max}} - 1\right) . e^{-W}} \tag{4}$$

Where, (W) denotes weight matrix, (η_2) signifies solution of current population. The position updating the process presents dynamic inertia weight to more balance among convergence speed with population diversity of BBOA.

Step 6:Termination

The weight parameter values (W, η_2) of generator from Memristive Bi-neuron Hopfield Neural Network is enhanced by help of BBOA, iteratively repeat the step 3 until fulfil halting criteria $X = X + 1$ is met, Then MBHNN predicting the sentimental analysis of social relationships in elderly smart homes with higher accuracy by lessening the computational time with error.

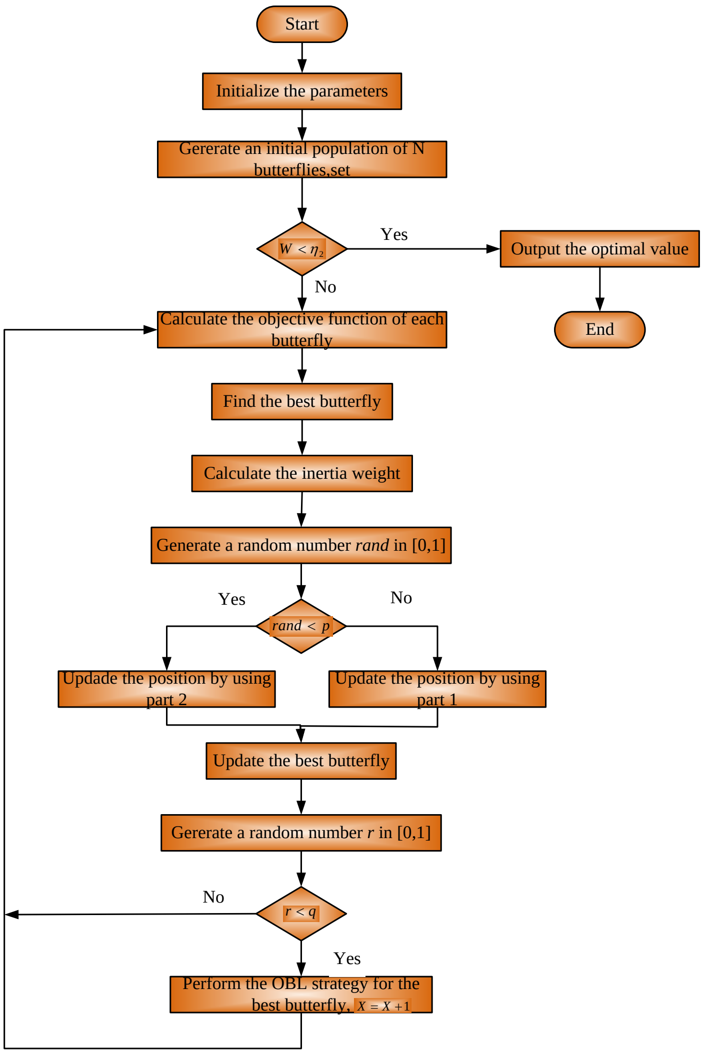

Figure2: Flowchart for BBOA for optimizing MBHNN parameter

IV. RESULT WITH DISCUSSION

Experimental results of SASR-MBHNN-BBOA technique have predicting the sentiments in elderly smart home. Implementation work was carried out Intel(R) core(TM) i7 CPU M60 @ 2.80 GHz in Python. It is evaluated by using several performance metrics like accuracy, precision, recall, F1-score, ROC are analysed. The outcomes of SASR-MBHNN-BBOA technique are analysed with existing methods likes SASR-CNN-SHA, SASR-ML-IECR and SASR-DNN-EASA.

A. Performance metrics

This is evaluated to scale effectiveness of proposed technique. To achieve this, following confusion matrix is crucial.

1) Accuracy

The value of accuracy is calculated as ratio of the count of samples accurately categorized by scheme with total count of samples.

2) Precision

It analyses the predictive value of sample, which positive or negative depends upon class for which is computed; in other terms, it assesses samples' predictive power.

3) F1 - score

A composite measure called F1-score which advantages approaches with better sensitivity and challenges for approaches with better specificity.

4) Recall

It is a metrics that computes predictions made by correct number of positive predictions made by total positive predictions.

5) ROC

ROC expressed as ratio among changes in one variable comparative to equivalent change in another, graphically; rate of change represents slope of line.

B. Performance analysis

The simulation results of SASR-MBHNN-BBOA method are showed in Figure 3 to 7. The SASR-MBHNN-BBOA method is analysed with existing SASR-CNN-SHA, SASR-ML-IECR, and SASR-DNN-EASA models.

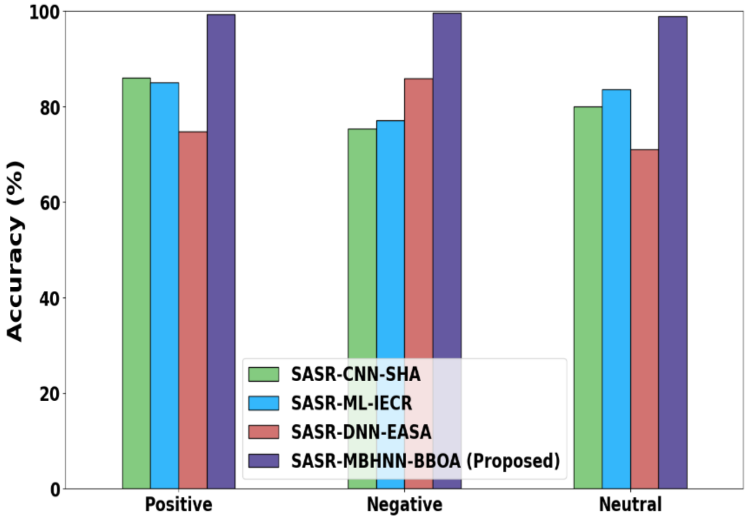

Figure 3: Accuracy analysis

Figure 3 displays accuracy analysis when number of epochs increased, the classification accuracy increased as well. In this context, the proposed SASR-MBHNN-BBOA method attains 20.8%, 19.5%, and 29.6% higher accuracy for positive; 16.1%, 37.2%, and 28.8% higher accuracy for negative; 17.9%, 20.7%, and 25.6% higher accuracy for neutral as analysed with existing methods SASR-CNN-SHA, SASR-ML-IECR, and SASR-DNN-EASA respectively.

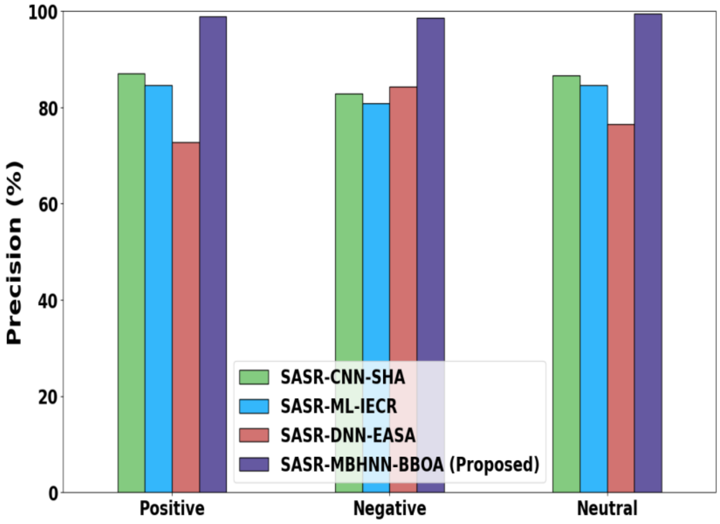

Figure 4: Precision analysis

Figure 4 shows precision analysis. It is frequently taken into account in conjunction with other measures to offer a complete data. In this context, the proposed SASR-MBHNN-BBOA method attains 28.8%, 22.5%, and 32.6% higher Precision for positive; 23.3%, 16.8%, 28.7% higher precision fornegative; 16.9%, 25.7%, and 32.6% higher precision for neutral as analysed with existing methods SASR -CNN-SHA, SASR-ML-IECR, and SASR-DNN-EASA respectively.

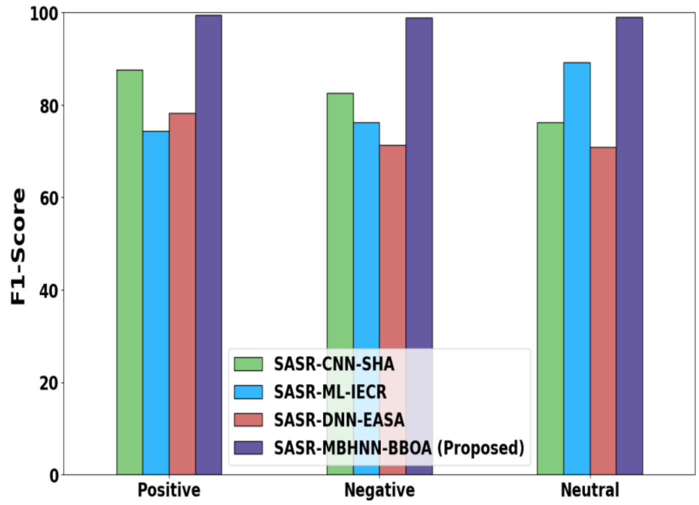

Figure 5: F1-score analysis

Figure 5 displays F1-score analysis. The F1 score comes in handy especially in cases where distribution of classes isn't uniform. In this context,SASR-MBHNN-BBOA method attains 29.3%, 35.5%, and 24.7% higher F1-score for positive; 22.6%, 31.8%, 16.7% higher F1-score for negative; 16.9%, 30.7%, and 26.6% higher F1-score for neutral as analysed with existing methods SASR -CNN-SHA, SASR-ML-IECR, and SASR-DNN-EASA respectively.

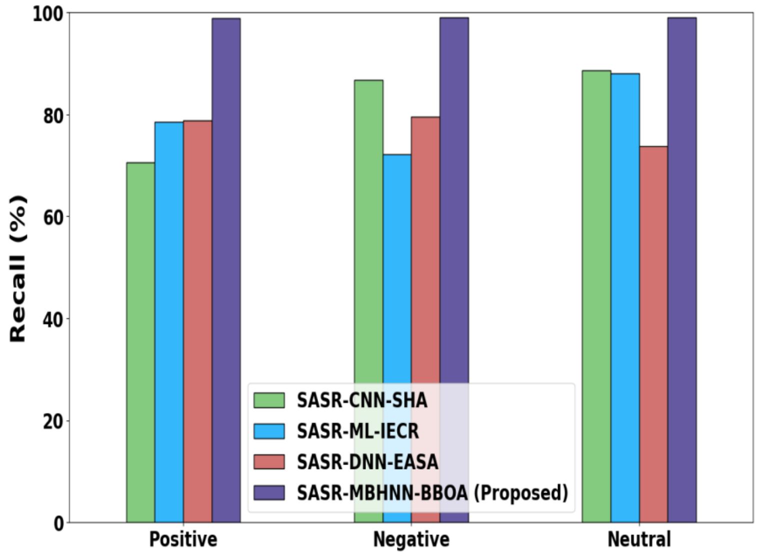

Figure 6: Recall analysis

Figure 6 shows recall analysis. It is a metrics computes predictions made by exact number of positive predictions made by total positive predictions. The proposed SASR-MBHNN-BBOA method attains 15.5%, 27.4%, and 18.2% higher Recall for positive; 20.7%, 19.2%, 17.8% higher Recall for negative; 18.9%, 22.7%, and 21.6% higher Recall for neutral as analysed existing methods SASR -CNN-SHA, SASR-ML-IECR, and SASR-DNN-EASA respectively.

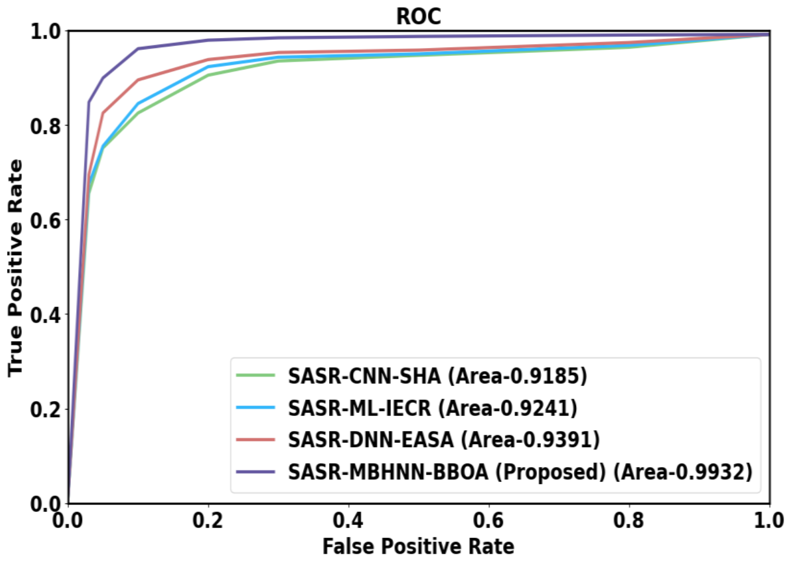

Figure 7: ROC analysis

Figure 7 shows the performance of ROC analysis. It expressed as ratio among changes in one variable comparative to corresponding change in another. The SASR-MBHNN-BBOA method attains 29.8%, 34.5%, and 19.6% higher ROC for positive; 27.3%, 25.8%, 18.7% higher ROC for negative; 17.9%, 20.7%, and 25.6% higher ROC for neutral as compared to the existing methods SASR -CNN-SHA, SASR-ML-IECR, and SASR-DNN-EASA respectively.

C. Discussion

The study of "Modeling and Sentiment Analysis of Social Relationships in Elderly Smart Homes Using Deep Learning" is a ground-breaking endeavour that signals a shift in perspective on the well-being of senior people in smart home environments. DL approaches for sentiment analysis have ability to reveal rich emotional subtleties contained in social interactions. This study addresses not just the technical implementation of deep learning models, but also ethical concerns and the need for customisation adapted to the special needs of the elderly. Addressing issues such as data privacy and model interpretability, the research contributes to a more comprehensive understanding of this technology's strengths and limitations. The practical implications go beyond theoretical frameworks, shedding light on how the findings could lead the creation of personalized assistive devices for the aged. The forward-looking debate anticipates future research directions, emphasizing model development and ethical implications for responsible deployment in elderly smart homes.

V. CONCLUSION

In this section, Modeling and Sentiment Analysis of Social Relationships in Elderly Smart Homes Based on Graph Neural Networks (SASR-MBHNN-BBOA) was effectively executed. The SASR-MBHNN-BBOA is executed in Python. The SASR-MBHNN-BBOA is used to predicting the sentiments automatically in Elderly Smart Homes. Evaluating the performance of approach, the results highlight distinct improvements and achieving 22.6%, 31.8%, 16.7% higher F1-score, 29.8%, 34.5%, and 19.6% higher ROC are compared with existing methods like SASR -CNN-SHA, SASR-ML-IECR, and SASR-DNN-EASA respectively. In the future, this research will include a broader range of themes, nations, accents, age, gender categories. The goal is to create application can be deployed in real world and improve consumers' real-time identification. Also, efforts will be made to extract a variety of acoustic signals by mixing features from innovative classification methods for Speech Emotion Recognition. Other metrics added to completely assess performance of categorization models.

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