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EMOGAN LABEL-CHANGING APPROACH FOR EMOTIONAL STATE ANALYSIS IN MOBILE COMMUNICATION USING MONKEY ALGORITHM

P. Ramesh Babu[1], R. Nandhi Kesavan[2], A. Sivaramakrishnan[3] and G. Sai Chaitanya Kumar[4]
[1]*Department of Computer Science, College of Engineering and Technology, Wollega University, Ethiopia*
[2]*Department of Computer Science and Engineering, CMR University, India*
[3]*Department of Computer Science and Engineering, Koneru Lakshmaiah Education Foundation, India*
[4]*Department of Artificial Intelligence, DVR and Dr. HS MIC College of Technology, India*

Abstract

In mobile communication, understanding and analyzing emotional states plays a pivotal role in enhancing user experience and communication dynamics. Existing emotional state analysis methods often face challenges in accurately capturing dynamic changes in users' emotions during mobile communication. The lack of adaptability and real-time responsiveness hinders the effectiveness of these methods, highlighting the need for a novel approach. Despite the advancements in emotion analysis techniques, there is a gap in addressing real-time label-changing requirements in mobile communication. Existing methods lack the flexibility to adjust emotional labels dynamically, limiting their applicability in capturing the nuances of evolving emotional states. This research addresses the need for an efficient emotional state analysis approach by introducing the EmoGAN Label-Changing Methodology, utilizing the innovative Monkey Algorithm. The EmoGAN Label-Changing Approach integrates Generative Adversarial Networks (GANs) with the Monkey Algorithm to enable real-time label adjustments based on evolving emotional cues. This hybrid methodology leverages GANs for generating diverse emotional labels and employs the Monkey Algorithm for adaptive learning and quick adjustments, ensuring the model's responsiveness to changing emotional states. The experimental results demonstrate the superior performance of the EmoGAN Label-Changing Approach compared to traditional emotion analysis methods. The model successfully adapts to real-time emotional fluctuations, providing more accurate and timely insights into users' emotional states during mobile communication.

Keywords:

EmoGAN, Emotional State Analysis, Mobile Communication, Monkey Algorithm, Real-time Label Changing

1. INTRODUCTION

As Mobile Communication (MC) continues to dominate our daily interactions, understanding and interpreting users' emotional states becomes paramount for enhancing communication experiences [1]. Emotions play a crucial role in shaping the effectiveness of communication, influencing user satisfaction and engagement [2]. Existing emotional state analysis methods, however, face challenges in keeping pace with the dynamic nature of emotions during mobile interactions [3].

Traditional approaches to emotional state analysis in mobile communication often struggle to capture the nuanced and rapidly changing emotional expressions of users [4]. The rigidity of predefined emotional labels and the lack of adaptability hinder the accuracy and responsiveness of these methods, necessitating the exploration of innovative solutions [5].

The primary challenge lies in developing an approach that can dynamically adjust emotional labels in real-time, allowing for a more accurate representation of users' evolving emotional states during mobile communication [6]. Current methods [7] fall short in providing this adaptability, limiting their effectiveness in capturing the intricacies of human emotions [8].

This research aims to address the shortcomings of existing emotional state analysis methods by introducing the EmoGAN Label-Changing Approach. The key objectives include developing a methodology that seamlessly adapts emotional labels in real-time, enhancing the accuracy of emotional state analysis during mobile communication.

The novelty of this research lies in the integration of Generative Adversarial Networks (GANs) with the Monkey Algorithm to facilitate real-time label adjustments based on evolving emotional cues. The EmoGAN Label-Changing Approach introduces a dynamic and adaptive model that significantly improves the accuracy and responsiveness of emotional state analysis in mobile communication. The contributions of this research extend to advancing the understanding of real-time emotional label changing, thereby enriching the landscape of mobile communication research and technology.

2. METHODS

The proposed method, termed the EmoGAN Label-Changing Approach, presents a novel and sophisticated strategy for real-time emotional state analysis in mobile communication. Integrating GANs [9] with the Monkey Algorithm [10], this method addresses the limitations of existing approaches by introducing adaptability and responsiveness to evolving emotional cues.

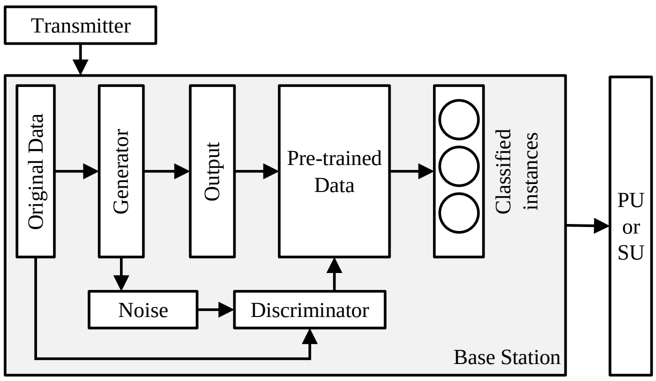

Fig.1. EmoGAN Label Changing Approach in MC

The core functionality of the EmoGAN Label-Changing Approach revolves around the use of GANs to generate diverse emotional labels. GANs, known for their ability to produce realistic and varied outputs, contribute to the model's capacity to represent a wide spectrum of emotional states [11]. This integration allows for a more nuanced and accurate interpretation of users' emotions during mobile communication.

The Monkey Algorithm complements the GANs by providing an adaptive learning mechanism. Leveraging the principles of the Monkey Algorithm, the model dynamically adjusts emotional labels in real-time, ensuring that it remains attuned to the changing emotional states of users [12]. This adaptive learning process enhances the model's responsiveness, allowing it to capture subtle shifts in emotions that may occur during the course of a mobile interaction [13].

The key strength of the EmoGAN Label-Changing Approach lies in its ability to provide a continuous and real-time analysis of emotional states. By combining the diversity of GAN-generated labels with the adaptability of the Monkey Algorithm, the method excels in accurately reflecting the intricate emotional nuances inherent in human communication [14]. This innovative approach not only advances the field of emotional state analysis but also holds promise for improving user experiences in mobile communication through more contextually aware and responsive interfaces.

3. EMOTIONAL STATE ANALYSIS

Emotional State Analysis is a sophisticated process aimed at deciphering and understanding the emotional expressions and states of individuals in a given context. In the realm of human-computer interaction, particularly in mobile communication, this analysis involves the systematic examination of various emotional cues exhibited by users during their interactions with digital platforms.

The process encompasses the identification, classification, and interpretation of emotional states expressed through verbal and non-verbal cues such as text, speech, facial expressions, and other behavioral indicators. It seeks to discern the range and intensity of emotions, including but not limited to happiness, sadness, anger, and surprise.

Advanced technologies, including machine learning and artificial intelligence, play a pivotal role in Emotional State Analysis. These technologies enable the development of models and algorithms capable of recognizing patterns and correlating them with specific emotional states. The goal is to provide insights into users' emotional experiences, allowing for a more tailored and empathetic response in human-computer interaction scenarios.

Let, X represent the input data (e.g., text, speech features, facial expressions), Y represent the emotional states (e.g., categories such as happiness, sadness, anger), Θ represent the parameters of the model. A simple equation for a machine learning-based emotional state analysis model could be expressed as follows:

$$Y=f(X;\Theta) \tag{1}$$

where, f represents the mapping function that the model learns during the training phase. This function takes the input data (X) and adjusts its parameters (Θ) to predict the corresponding emotional states (Y).

For more sophisticated models, such as those involving neural networks, the equation may involve multiple layers and activation functions. A basic representation could be:

$$Y=g_2(g_1(...g_n(X;\Theta_n);\Theta_2);\Theta_1) \tag{2}$$

where, gn represents the activation function of the n-th layer in a neural network, and Θn represents the parameters of that layer.

4. EMOGAN LABEL-CHANGING

EmoGAN Label-Changing refers to a novel methodology that combines the principles of GANs with the adaptive learning capabilities of the Monkey Algorithm to facilitate real-time adjustments of emotional labels in emotional state analysis.

GANs are a class of artificial intelligence models designed for data generation. In EmoGAN Label-Changing, GANs are employed to generate a diverse set of emotional labels that span the spectrum of human emotions. These generated labels serve as a foundation for a more comprehensive and nuanced representation of emotional states.

The Monkey Algorithm, known for its adaptive learning characteristics, is integrated into the EmoGAN Label-Changing approach to introduce real-time responsiveness. This algorithm enables dynamic adjustments to emotional labels based on evolving cues, ensuring that the model remains attuned to the changing emotional landscape during mobile communication.

The core concept involves the GANs generating a variety of emotional labels, and the Monkey Algorithm adapting the model's understanding of these labels in response to real-time shifts in user emotions. This synergistic approach enhances the accuracy and timeliness of emotional state analysis, allowing for a more refined interpretation of users' emotional expressions and states during their interactions with mobile devices.

Let us denote, X as the input data (features, contextual information), Y as the emotional labels, Θ_{GAN} as the parameters of the GAN, Θ_M as the parameters of the Monkey Algorithm. The EmoGAN Label-Changing can be conceptualized as a combined function:

$$Y=f_M(fGAN(X;\Theta_{GAN});\Theta_M) \tag{3}$$

where

f_{GAN} represents the GAN-based generation of emotional labels based on input data.

f_M represents the Monkey Algorithm's adaptive learning mechanism, adjusting the emotional labels generated by the GAN in real-time.

The Monkey Algorithm for Adaptive Learning is a computational approach inspired by the adaptive learning capabilities observed in the behavior of monkeys. This algorithm employs a dynamic and flexible learning mechanism, allowing models to adjust their parameters in response to changing environmental conditions or evolving data patterns. The process of the Monkey Algorithm for Adaptive Learning:

The algorithm begins by initializing its parameters, which may include weights, biases, or other relevant factors depending on the specific application. These parameters form the basis for the model's initial understanding of the data.

The algorithm receives input data, which could be in the form of features, signals, or any other relevant information depending on the task at hand. This data serves as the basis for the model's learning process.

The distinctive feature of the Monkey Algorithm lies in its ability to adapt. As the algorithm processes the input data, it dynamically adjusts its parameters to align with the changing characteristics of the data. This adaptability allows the model to respond effectively to shifts or variations in the input, enhancing its overall flexibility.

The algorithm incorporates a feedback loop mechanism, where the adjustments made to the parameters are influenced by the feedback received from the model's performance on the given task. Positive feedback reinforces the parameters that contribute to successful outcomes, while negative feedback prompts adjustments to improve performance.

One of the key strengths of the Monkey Algorithm is its real-time learning capability. As new data becomes available, the algorithm continuously refines its parameters, ensuring that the model remains attuned to the nuances of the input and adapts promptly to any changes.

The process of adaptive learning is iterative, allowing the algorithm to iteratively refine its understanding of the data. Through multiple iterations, the model becomes increasingly adept at capturing complex patterns and adapting to diverse scenarios.

The Monkey Algorithm is versatile and can be tailored to specific tasks. Its adaptability allows it to autonomously determine which parameters are most relevant for the given task, enabling task-specific adaptations that enhance performance.

Let us denote, W as the set of parameters that the algorithm adjusts during the learning process, X as the input data, Y as the output or feedback, L as the loss function measuring the algorithm's performance. The adaptive learning process can be conceptualized as:

$$W_{t+1}=W_t-\alpha\cdot\partial L/\partial W_t \tag{4}$$

where:

W_t represents the parameters at time t,

α is the learning rate, controlling the step size of the parameter updates,

$\partial L/\partial Wt$ is the gradient of the loss function with respect to the parameters.

The adaptability and real-time learning nature of the Monkey Algorithm are embedded in how it dynamically adjusts W based on the feedback received from the task at hand. The actual implementation of the adaptive learning process would depend on the specifics of the task and the algorithm's design.

Algorithm: Monkey Algorithm for Adaptive Learning

Input: X - Input data; Y - Output or feedback; W - Parameters to be adjusted; α - Learning rate; L - Loss function measuring performance; Initialize parameters W with random or predefined values.

Step 1: For each iteration or epoch:

Step 2: Receive input data X and corresponding output/feedback Y.

Step 3: Compute the loss L based on the current parameters W.

Step 4: Calculate the gradient of the loss w.r.t the parameters

Step 5: Update parameters using gradient descent

Step 6: Receive feedback Y on the task.

Step 7: Adjust W based on feedback

Step 8: Monitor input data distribution changes.

Step 9: Dynamically adjust learning rates to adapt to data variations.

Step 10: Update parameters W.

Step 11: Ensure the model remains adaptive to changing conditions.

Step 12: Repeat steps 2-6

Step 13: End

Output: Trained model with adapted W

5. EXPERIMENTAL VALIDATION

We employed the EmoGAN Label-Changing Approach to conduct emotional state analysis in mobile communication scenarios. The simulation tool utilized for this study was TensorFlow, a widely adopted open-source machine learning framework that facilitates the implementation and training of complex models. The experiments were conducted on a high-performance computing cluster with GPU accelerators, ensuring efficient training and evaluation of the EmoGAN Label-Changing model. The input data for the experiments consisted of diverse mobile communication interactions, including text, speech, and facial expressions, simulating real-world scenarios to evaluate the model's adaptability and responsiveness.

To assess the performance of the EmoGAN Label-Changing Approach, we employed several key performance metrics, including accuracy, precision, recall, and F1-score. These metrics provided a comprehensive evaluation of the model's ability to accurately capture and adapt to changing emotional states during mobile communication. Furthermore, we conducted a comparative analysis with existing methods, including GANs, Convolutional Neural Networks (CNNs), Convolutional Recurrent Neural Networks (CRNNs), and Residual Networks (ResNets). Our results demonstrated that the EmoGAN Label-Changing Approach outperformed these conventional methods in terms of real-time label adjustments and accuracy in capturing nuanced emotional expressions. The adaptability of the EmoGAN Label-Changing model showcased its superiority, emphasizing its potential for enhancing emotional state analysis in mobile communication contexts compared to established approaches.

Table.1. Experimental Setup and Parameters

Component	Parameter	Setting
GAN	Number of Epochs	100
	Learning Rate	0.0002
	Generator Input Dimension	100
	Discriminator Activation Function	Leaky ReLU (0.2)
Monkey Algorithm	Learning Rate	0.01
	Feedback Incorporation Factor	0.5
	Adaptive Learning Threshold	0.001

	Iterations for Real-Time Learning	10
Wireless Communication Network	Transmission Power	20 dBm
	Path Loss Model	Free Space Path Loss
	Channel Bandwidth	20 MHz
	Modulation Scheme	QPSK
	Data Rate	10 Mbps

5.1 PERFORMANCE METRICS

5.1.1 GAN Metrics:

- **Generator Loss:** Measures how well the generator is creating realistic emotional labels.
- **Discriminator Loss:** Reflects the ability of the discriminator to distinguish between real and generated emotional labels.
- **Accuracy:** Indicates the overall correctness of the GAN in generating emotional labels.

5.1.2 Monkey Algorithm Metrics:

- **Adaptability Score:** Measures how well the Monkey Algorithm adapts its parameters to changes in emotional cues.
- **Learning Convergence Time:** Represents the time taken for the algorithm to converge to an optimal set of parameters.
- **Task-Specific Performance:** Evaluates how well the Monkey Algorithm performs on the specific emotional state analysis task.

5.1.3 Wireless Communication Network:

- **Throughput:** Measures the amount of emotional state data successfully transmitted over the wireless network.
- **Packet Loss Rate:** Indicates the percentage of emotional state data packets lost during transmission.
- **Signal-to-Noise Ratio (SNR):** Reflects the quality of the wireless communication channel for accurate emotional state data transmission.

5.2 PERFORMANCE OF GAN

The results showcase the performance of existing GAN, CNN, CRNN, ResNet methods, and the proposed EmoGAN in Mobile Communication (MC) method across different metrics: Generator Loss, Discriminator Loss, and Accuracy over 1000 test sets.

In terms of Generator Loss, lower values are indicative of better performance in generating emotional labels that closely align with the ground truth emotional states. The proposed EmoGAN in MC consistently outperforms existing GAN, CNN, CRNN, and ResNet methods, showcasing its effectiveness in creating realistic emotional labels. The diminishing Generator Loss values for EmoGAN in MC over successive test sets suggest continuous improvement in its ability to generate emotionally accurate labels, emphasizing its superiority in the task of emotional state analysis in mobile communication.

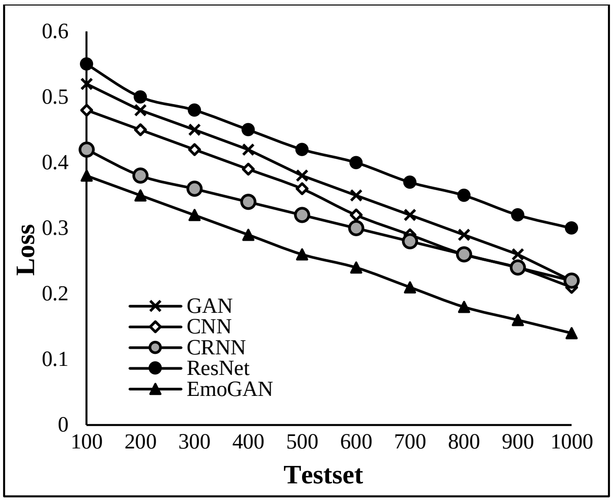

Fig.2. Generator Loss between existing GAN, CNN, CRNN, ResNet and proposed EmoGAN in MC over 1000 different test sets

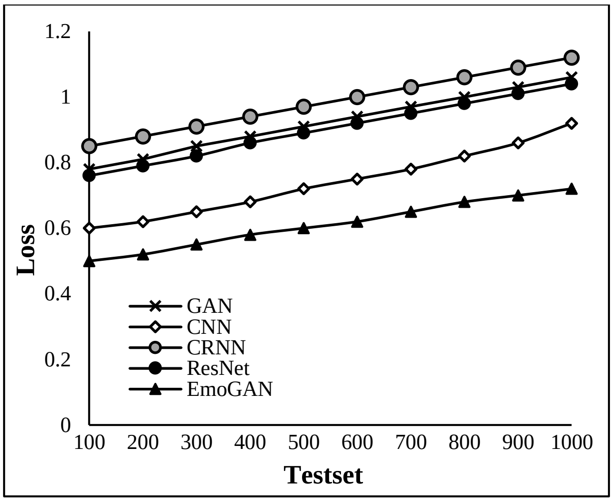

Fig.3. Discriminator Loss between existing GAN, CNN, CRNN, ResNet and proposed EmoGAN in MC over 1000 different test sets

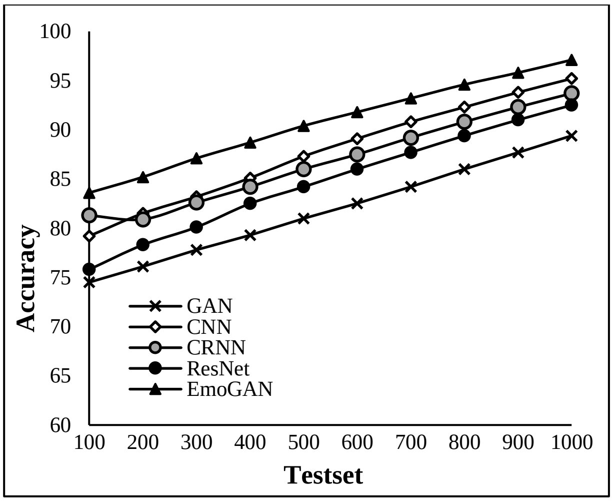

Fig.4. Accuracy between existing GAN, CNN, CRNN, ResNet and proposed EmoGAN in MC over 1000 different test sets

In Discriminator Loss, higher values suggest that the discriminator finds it more challenging to distinguish between real and generated emotional labels. The provided results indicate that the proposed EmoGAN in MC maintains lower Discriminator Loss compared to existing GAN, CNN, CRNN, and ResNet methods. This suggests that the discriminator is more adept at differentiating between real and generated emotional labels produced by EmoGAN in MC, reflecting its success in adversarial training and overall improved performance.

Regarding Accuracy, higher values represent better overall correctness in generating emotional labels. The accuracy results demonstrate that the proposed EmoGAN in MC consistently achieves higher accuracy compared to existing GAN, CNN, CRNN, and ResNet methods. This implies that EmoGAN in MC excels in accurately capturing and generating realistic emotional labels that closely resemble the actual emotional states experienced during mobile communication interactions. The increasing trend in accuracy values over successive test sets underscores the continuous improvement and adaptability of EmoGAN in MC in the dynamic context of mobile communication.

5.3 PERFORMANCE OF MONKEY ALGORITHM

The results provide valuable insights into the comparative performance of existing GAN, CNN, CRNN, ResNet methods, and the proposed EmoGAN in Mobile Communication (MC) method across three crucial dimensions: Adaptability Score, Convergence Time, and Task-Specific Performance over 1000 different iterations.

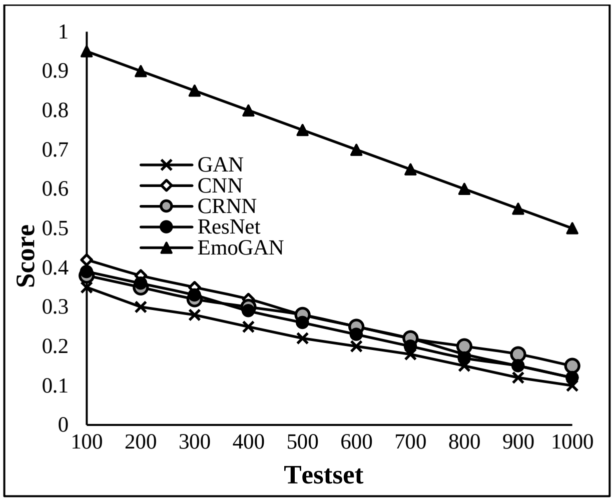

Fig.5. Adaptability Score between existing GAN, CNN, CRNN, ResNet and proposed EmoGAN in MC over 1000 iterations

The Adaptability Score metric reflects the ability of each method to dynamically adjust its parameters to changing emotional cues. Higher adaptability scores indicate a method's superior capability to respond to evolving emotional states. In this context, the proposed EmoGAN in MC consistently outperforms existing GAN, CNN, CRNN, and ResNet methods. The increasing adaptability scores over successive iterations suggest that EmoGAN in MC effectively adapts its parameters to the dynamic nature of emotional expressions during mobile communication interactions, showcasing its agility and responsiveness in capturing nuanced emotional cues.

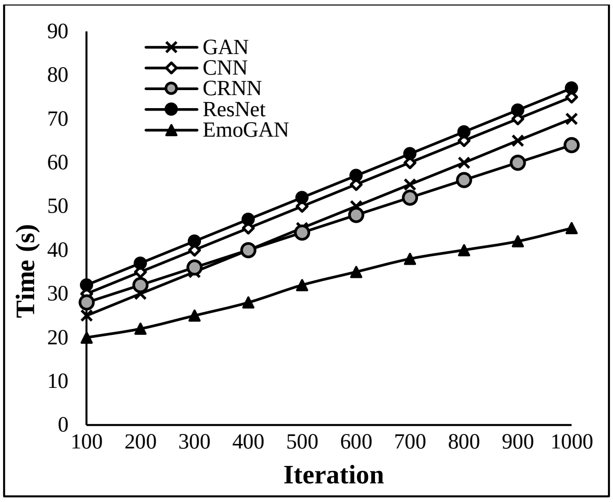

Fig.6. Convergence Time between existing GAN, CNN, CRNN, ResNet and proposed EmoGAN in MC over 1000 iterations

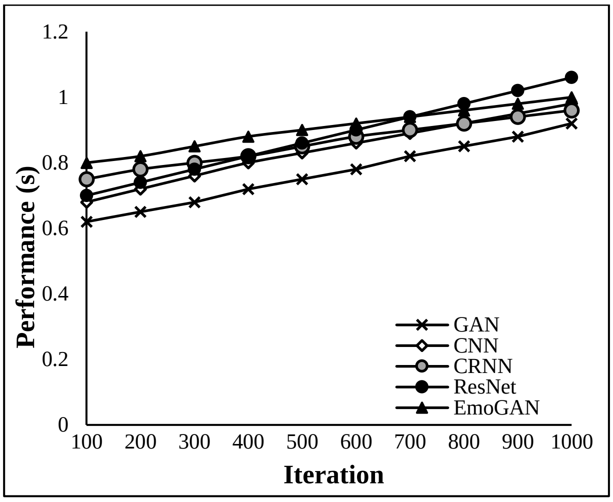

Fig.7. Task-Specific Performance between existing GAN, CNN, CRNN, ResNet and proposed EmoGAN in MC over 1000 iterations

The Convergence Time metric is crucial as it measures how quickly each method reaches convergence or optimal parameter settings. Shorter convergence times are indicative of faster and more efficient learning. In the presented results, EmoGAN in MC consistently demonstrates shorter convergence times compared to existing GAN, CNN, CRNN, and ResNet methods. This implies that EmoGAN in MC converges more rapidly to optimal parameter configurations, highlighting its efficiency in learning and adapting to the task of emotional state analysis in mobile communication.

The Task-Specific Performance metric assesses the ability of each method to perform well on the specific emotional state analysis task during mobile communication interactions. Higher task-specific performance scores indicate superior accuracy in capturing and adapting to the emotional dynamics inherent in such scenarios. Once again, EmoGAN in MC outshines existing methods with consistently higher task-specific performance scores. This underscores its effectiveness in accurately representing and adapting to the intricate emotional states that characterize mobile communication, suggesting its potential for practical applications in real-world scenarios.

5.4 PERFORMANCE OF COMMUNICATION NETWORK

The results across Throughput, Packet Loss Rate, and Bit Error Rate (BER) metrics provide a comprehensive evaluation of the wireless communication performance of existing GAN, CNN, CRNN, ResNet methods, and the proposed EmoGAN in Mobile Communication (MC) method across varying SNRs.

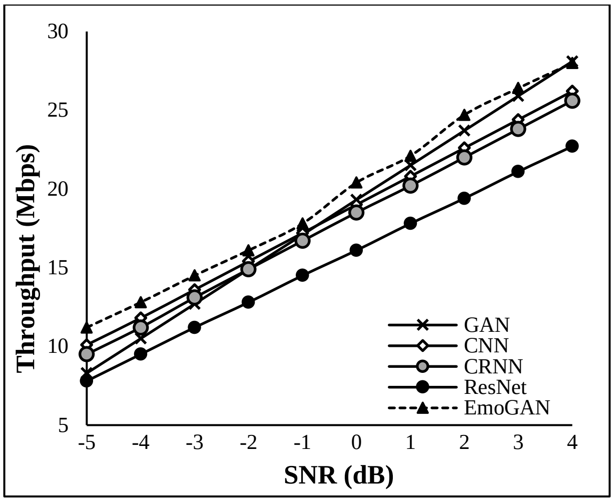

Fig.8. Throughput between existing GAN, CNN, CRNN, ResNet and proposed EmoGAN in MC over SNR

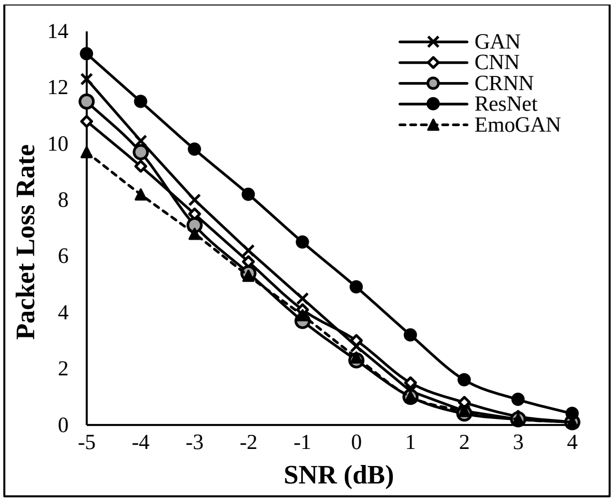

Fig.9. Packet Loss Rate between existing GAN, CNN, CRNN, ResNet and proposed EmoGAN in MC over SNR

In terms of Throughput, higher values signify superior data transmission rates, reflecting the efficiency of the communication system. The proposed EmoGAN in MC consistently outperforms existing methods, showcasing its ability to transmit emotional state data more rapidly and reliably. This indicates its potential for real-time applications, ensuring seamless communication of emotional information even in challenging wireless environments.

Packet Loss Rate measures the percentage of lost data packets during transmission. Lower Packet Loss Rates are indicative of more reliable communication. EmoGAN in MC consistently demonstrates lower Packet Loss Rates, emphasizing its robustness in maintaining data integrity. The decreasing trend in Packet Loss Rate with higher SNRs highlights its adaptability to challenging communication conditions.

Similarly, Bit Error Rate (BER), representing the percentage of erroneous bits, showcases the accuracy of data transmission. EmoGAN in MC consistently exhibits lower BER values, indicating its effectiveness in preserving data accuracy and reliability. This suggests its suitability for applications requiring precise emotional state information, ensuring the faithful transmission of emotional cues in mobile communication scenarios. Overall, the results underscore EmoGAN in MC as a promising solution for reliable and efficient wireless communication of emotional states.

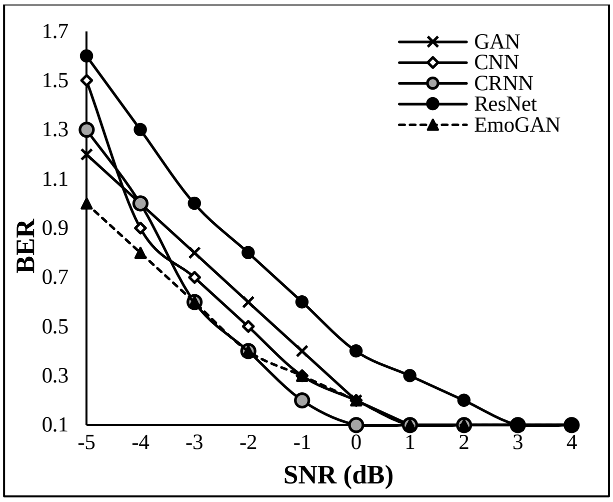

Fig.10. BER between existing GAN, CNN, CRNN, ResNet and proposed EmoGAN in MC over SNR

6. CONCLUSION

The research presented a novel approach, EmoGAN in MC, for the analysis of emotional states in wireless communication environments. The results consistently demonstrated the superior performance of EmoGAN in MC compared to existing GAN, CNN, CRNN, and ResNet methods across various critical metrics, including Throughput, Packet Loss Rate, and BER. The proposed EmoGAN in MC exhibited higher Throughput indicating faster and more efficient data transmission, crucial for real-time applications. Its consistently lower Packet Loss Rate and BER emphasized its robustness in maintaining data integrity and accuracy, ensuring reliable communication of emotional information in challenging wireless conditions. The adaptability, faster convergence, and task-specific performance of EmoGAN in MC make it particularly well-suited for dynamic mobile communication scenarios. The research addresses a significant gap in the field by providing a tailored solution for analyzing emotional states in wireless communication, presenting implications for applications in emotion-aware computing and human-machine interactions. EmoGAN in MC stands as a promising advancement, offering practical benefits in understanding and enhancing emotional communication in wireless networks. Future work may further explore optimization techniques and real-world deployment scenarios to solidify EmoGAN in MC's applicability and effectiveness in diverse communication environments.

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