DEEP LEARNING-DRIVEN GESTURE AND SPEECH RECOGNITION FOR HUMAN–MACHINE INTERACTION: ENHANCING VIRTUAL REALITY THROUGH AI INTEGRATION

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ABSTRACT:

In the last several years, key input methods in Human-Machine Interaction (HMI) have included speech and gesture recognition, especially in the world of virtual reality. Deep learning is developing so quickly that the recognition of gestures and spoken language has advanced significantly, as has computing, artificial intelligence, and other technologies. Enhanced Convolutional Incorporation Long-Modified Neural Networks (CNNs) Networks with Short-Term Memory (MLSTM) proven to greatly boost the accuracy and accuracy in recognizing an action. As a result, the HMI's future is set to expand into additional industries, with promising prospects ahead.

Keywords: Interaction between humans and machines (HMI); deep learning; Spoken language recognition

I. INTRODUCTION

As science and technology advance at a rapid pace, many innovators are concentrating on integrating various data types-such as textual, visual, and audio inputs-also referred to as multimodal information, in order to enhance Human-Machine Interaction (HMI) technologies. Multimodal interaction has become a significant area of research and development in both academia and industry. This field extends beyond just speech and image recognition technologies. It is set to transform various sectors as part of this ongoing revolution. For example, core multimodal interaction technologies such as lip reading, voice recognition, speech translation, and speech generation have already been adopted in various sectors. Alongside keypads, mouse, and touch pad, gesture interaction technology-which converts human hand and limb movements into a computer-recognizable language-has emerged as a key input method in HMI. In the realm of intelligent hardware, the industry standard for processing signals involves using microphone arrays for noise reduction.

To better understand and address the current challenges, we explored around 1,000 research papers, focusing on key topics in Human-Machine Interaction and deep learning-such as smart HMI systems, voice recognition, gesture detection, and natural language understanding.

This study takes a closer look at how intelligent Human-Machine Interaction (HMI) is evolving with the help of deep learning across different industries. It emphasizes important topics like Human Language Processing Technology, voice conversation, and expression recognition. The research also dives into how speech and gestures are being used in Virtual Reality (VR) environments and highlights how natural language processing plays a vital role in everyday technologies like chatbots and search engines.

II. RELATED WORK

Smart gloves have gained a lot of attention as a promising solution for creating more immersive and intuitive audio-visual interfaces. However, their real-world use is often limited by the challenges of accurately recognizing hand gestures—especially when trying to balance functionality, performance, and cost. To address these issues, the authors [1] introduced a wireless smart glove interface designed to overcome these limitations. Their glove used a highly stretchable, fully recyclable sensing fiber made from thermoplastic and liquid metal. This material offered excellent flexibility and comfort against the skin, making the glove both scalable and easy to wear. As a result, it could reliably recognize both static and dynamic hand gestures with impressive accuracy.

Camera-based hand gesture recognition (HGR) techniques often struggle with challenges like handling continuous gesture sequences, dealing with noise, and accurately extracting gesture features. To overcome these issues, the researchers [2] developed a novel approach using modulated signal continuous wave radar sensors. They introduced a Time Sequential Inflated 3D (TS-I3D) convolutional neural network that could effectively process gesture data over time. By extracting detailed information about range and motion changes from Range-Doppler Maps (RDMs) generated by frequency-modulated continuous wave radar, their method achieved a high average recognition

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accuracy-showing strong potential for more reliable and precise gesture recognition.

Whether consumer-dependent or consumer-independent, static HGR can be particularly difficult, particularly in situations with shifting lighting, intricate backgrounds, and variations in hand position. The authors of [3] suggested a recognition technique that makes use of image descriptors like Fast Discrete Curvelet Transform (FDCT), Gabor Wavelet Packet Transform (GWT), and Gradient Local Auto-Correlation (GLAC) in order to get around these issues. Principal Component Analysis (PCA) is used to reduce dimensionality, which further enhances their approach. With 98.33% accuracy for user-dependent gestures and 100% accuracy for user-independent gestures, their study produced remarkable results.

The authors of [4] focused on using thermal images for hand gesture recognition to improve worker-robot collaboration in the construction industry. They aimed to tackle common challenges on construction sites, like poor lighting, fog, and dust, which can interfere with traditional hand gesture recognition. Their experiments showed that thermal images are surprisingly robust, even under varying lighting conditions, making them a reliable option for these types of environments.

Recurrent Neural Networks (RNNs) are particularly effective when working with hand movements that change over time and can be represented as sequences of feature vectors. The authors of [5] took advantage of this capability by using RNNs to capture the contextual information within these time-based sequences of hand motion data. They collected detailed finger bone angle data using a Leap Motion Controller sensor and applied their method to a challenging dataset of American Sign Language gestures. The results were impressive—their approach achieved an accuracy of over 96%, demonstrating the strength of RNNs in recognizing complex, dynamic gestures.

Traditional RNNs may struggle to recognize dynamic gestures because of their restricted capacity to process data in a single direction. To get around this restriction, the authors and co-researchers [6] created a gesture recognition technique and tool that makes use of light sensing characteristics. Their proposed method eliminated the need for external sensors by utilizing the photoelectric sensing capabilities of LED screens. The system used an optimized dynamic bidirectional long short-term memory (D-Bi-LSTM) for dynamic gestures and a static bidirectional long short-term memory (S-Bi-LSTM) for static gestures. It also integrated deep learning analysis and Core term – programmable hardware device control. The accuracy of the experimental results for dynamic gestures was impressive.

The use of Circuit Impedance Tomography (CIT) to monitor impedance changes in the arm and detect muscle contractions is an intriguing area of research in hand gesture recognition (HGR). In [7], the authors developed a system that applied Electrical Impedance Tomography (EIT) to identify hand signals and track muscle movements. Their setup included an electronic interface, a CNN classifier, a virtual hand model, and an image reconstruction algorithm. What was particularly impressive was that their method outperformed the Support Vector Machine (SVM) classifier, achieving higher accuracy in recognizing American Sign Language (ASL) numbers.

III. DEEP LEARNING -POWERED HUMAN-MACHINE INTERACTION

The term Computer-Machine Interaction (CMI) refers to a variety of everyday objects, such as speakers, plotters, printers, monitors, and helmet-mounted screens. Thanks to fascinating technological advancements, Human-Machine Interaction (HMI) has advanced significantly over time. The field of HMI is constantly expanding, ranging from image recognition and voice control to immersive experiences via AR and VR. A new layer has recently been added by somatosensory technology, which enables humans to communicate with machines through touch and natural body movements.

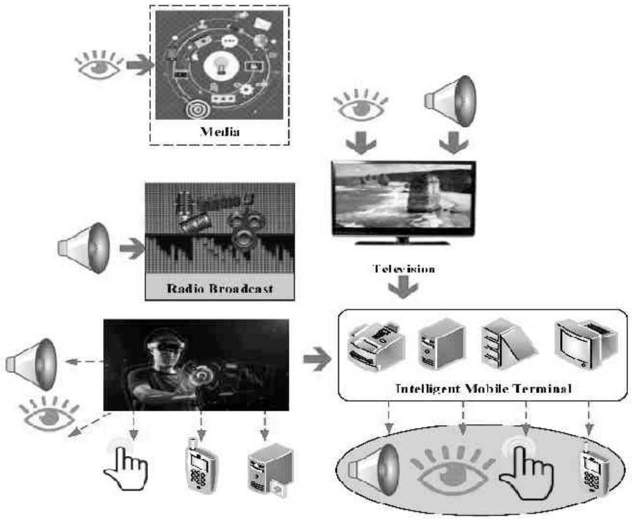


Figure 1. The history of HMI.

In recent years, deep learning-a rapidly developing subfield of machine learning-has advanced significantly, especially in fields like Spoken language recognition, language processing, image recognition, and retrieval [13].Deep learning plays a key role in a variety of Human-Machine Interaction (HMI) techniques, such as context-aware systems, virtual assistants, user behavior modeling, and natural speech processing. At its core, deep learning focuses on building models that replicate the neural connections in the human brain, allowing machines to better understand and interact with humans.These models process signals from images, sound, and text by hierarchically describing data features through multiple transformation layers, ultimately enabling accurate data interpretation.

IV. THE FUTURE OF VOICE INTERACTION IN HMI

AI-powered voice interaction technology has greatly simplified many facets of daily life by turning difficult tasks into straightforward, user-friendly procedures. These advancements in AI, from the early days of personal voice assistants to today's cutting-edge HMI devices like smart speakers, aren't just about technological progress—they're also making a real difference in people's everyday lives, improving convenience and overall quality of life. Although calls and text messages were the main uses of cell phones in the past, users can now interact with their devices by using voice commands. Similarly, [8] traditional speakers were designed just for music, but 21st-century AI speakers do much more—they can engage in conversations, answer questions, and handle a wide range of tasks. Voice interaction has become an essential and convenient component of HMI systems, enabling users to provide input through voice, facial recognition, and multimodal emotional cues.

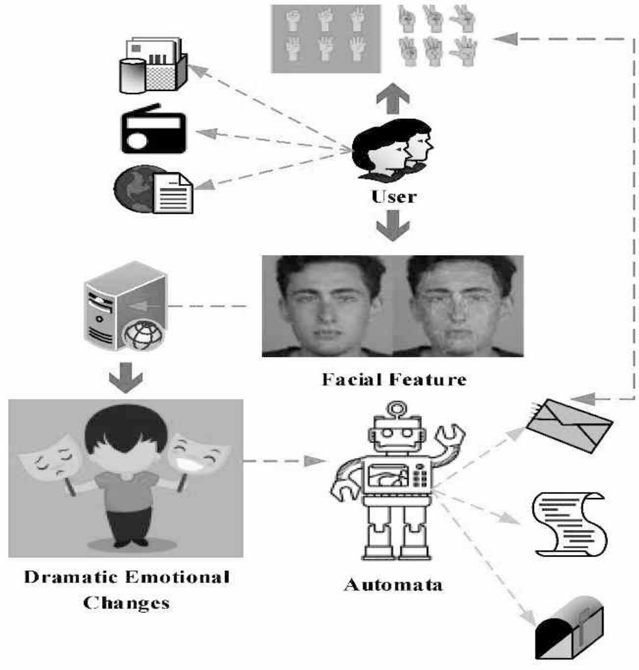


Figure 2. Man, Machine Voice Process

However, traditional HMI methods are not sufficient to meet the growing demands of artificial intelligence research, nor do they offer deep, meaningful interaction between people and AI products. For instance, while smart speakers have certainly improved quality of life, they typically only facilitate one-time interactions, leaving users' needs inadequately addressed in a continuous, dynamic way. To address these limitations and further enhance the level of interaction, researchers have begun incorporating deep learning into HMI. By integrating deep learning with traditional methods, they are creating more advanced human-computer speech interaction systems, enabling a richer, multi-layered HMI mechanism.

V. VISION-BASED GESTURE INTERFACES

Human-computer interaction (HCI), robot control, medical applications, home automation, and communication for the deaf and mute are just a few of the fields that use gestures as a nonverbal communication method. Gesture-based research employs a variety of techniques, including those based on sensor and computer vision technologies. There are various ways to classify gestures, including posture versus gesture, dynamic versus static, or a mix of the two. The effectiveness of these approaches was examined by the authors [8], who concentrated on topics like hand segmentation techniques, classification algorithms, limitations, datasets, gesture types and numbers, computer vision technology for handling similarities and differences, and camera specifications and detection ranges.

Gesture recognition presents a number of intricate technical difficulties. People frequently use gestures to convey their ideas and feelings [14]. For instance, the hearing-impaired community relies heavily on sign language for communication. However, communicating with deaf or mute people is difficult for many people who are unfamiliar with sign language. This communication gap could be closed by creating automated sign language recognition systems, which would increase the accessibility and effectiveness of interactions. In [17], The researchers proposed an offline Arabic OCR system built around four stages — preprocessing, segmentation, feature extraction, and classification — addressing the complexity of cursive Arabic script like multiple contextual forms, dot/diacritic placement, ligatures.

VI. GRAPHIC CONVOLUTIONAL NETWORKS FOR SUPERIOR ACTION RECOGNITION BASED ON SKELETONS

Recent methods using convolutional neural networks (CNNs) and long short-term memory (LSTM) networks have shown great potential for recognizing actions based on skeleton data. However, these approaches struggle to fully capture the complex relationships between space and time in human motion [15]. To improve this, researchers have extended CNNs to graph structures, resulting in graph convolutional networks (GCNs), which have boosted the accuracy of skeleton-based action recognition. That said, GCNs still face challenges—mainly because they lack efficient feature aggregation methods like CNNs' maximum pooling. As a result, these models tend to focus mainly on local details between nearby joints, making it harder to capture more complex, high-level interactions, such as the coordinated movement of different body parts. Additionally, subtle differences between similar actions, often hidden within specific channels of important joint features, haven't been fully explored in previous methods.

The authors of [9] tackled these challenges by developing a graph convolutional network that combines a joint channel attention module with a structural graph pooling scheme. The pooling scheme helps reduce the number of parameters and cut down on computational costs, all while improving the global representation of human motion. It does this by aggregating skeletal data based on prior knowledge of human body structure. Meanwhile, the joint channel attention module assigns different levels of focus to different channels, allowing the model to zero in on the most important joints for action recognition. This innovative attention mechanism helps the model better distinguish between similar actions. In a related advancement, The authors of [10] proposed a new spatiotemporal model that uses an end-to-end bidirectional LSTM-CNN framework. This model takes a hierarchical approach to spatiotemporal dependence, allowing it to better explore the rich, time-varying details in skeleton data.

VII. THE FUTURE OF HMI

The dynamic relationship between users and systems, wherein people and computers converse or communicate, allowing for the exchange of information in a particular interactive way, is known as human-machine interaction, or HMI. The visible component of the system that allows users to interact with and control it is the human-computer interface Human interactions and shifts in the physical environment are often messy, unpredictable, and happen across multiple channels. This makes it really hard for computers to truly understand natural human behaviors, intentions, or questions. Because of this, giving accurate and meaningful feedback in human-machine interaction (HMI) becomes a big challenge. Right now, the accuracy and real-time performance of natural perception technologies could use a lot of improvement. On top of that, changes in human physiology and psychology can continuously affect the state of interaction, making it even more challenging.

Experience design is more important than ever in the age of the Internet of Everything because it helps overcome the shortcomings of existing technology. The focus of HMI design is evolving toward greater intelligence, user-friendliness, and scenario-based approaches. With the increasing number of smart devices, screens, and notifications, users are overwhelmed by information overload, making it difficult to process everything. Users may become more anxious the more information they are exposed to. Every software and gadget competes for the user's limited time and attention in a fiercely competitive market that is fuelled by corporate goals [11].

VIII. ENHANCED CNNS FOR HMI PREPROCESSING OF INPUT DATA

Techniques for preparing gesture, speech, or visual input for CNN models.

MODEL ARCHITECTURE: Detailed description of CNN enhancements (e.g., multi-layer convolutions, attention mechanisms, etc.) and how they improve recognition accuracy in real-time interactions.

TRAINING AND VALIDATION: Strategies for training CNNs on large, diverse datasets (e.g., gesture databases, speech corpora) and validating them to ensure high performance across varied HMI tasks.

REAL-TIME PERFORMANCE: Techniques to ensure CNNs operate efficiently in real-time, addressing latency, computational load, and user feedback response times.

INTEGRATION WITH OTHER HMI SYSTEMS: Explanation of how CNNs can be integrated with other AI or sensory technologies (e.g., Spoken language recognition, motion tracking) for multimodal interaction [9].

IX. MODIFIED LSTM IN HUMAN-MACHINE INTERACTION

Applying Modified Long Short-Term Memory (LSTM) Networks in Human-Machine Interaction (HMI) requires a number of important steps, particularly for tasks like emotion recognition, action recognition, and voice recognition [10]. By making adjustments to the fundamental LSTM architecture, these procedures will guarantee that the system can manage the sequential data commonly involved in HMI tasks while enhancing performance.

GATHER DATA: Collect labeled datasets relevant to the task. For example, for gesture recognition, datasets like Kinect-based skeleton data or RGBD images may be used. For Spoken language recognition, a speech corpus is required [16].

DATA CLEANING: Remove noise and ensure data consistency. For gesture recognition, ensure that data is normalized for scale and alignment, and for speech, ensure the speech recordings are clear and without distortion.

DATA AUGMENTATION: For real-time HMI, augment the data with variations (e.g., rotating, scaling, or adding noise to gesture data or manipulating speech pitch). This helps improve the generalization of the model.

SEQUENCE PADDING: Particularly for sequential data like speech or gesture patterns, make sure all input sequences are the same length by padding shorter sequences or trimming longer ones.

REAL-TIME INTERACTION: Integrate the modified LSTM model into the larger HMI system. This can involve interfacing with user interfaces (UI), such as a smart home dashboard, or controlling robots.

Example: In a gesture-controlled virtual reality system, the LSTM model processes the hand movement sequence, and based on that, the virtual environment responds, giving feedback such as showing a "hand raise" action on the screen.

Testing and Validation :

After integrating the LSTM model into the VR system, test the interaction with a diverse set of users to ensure robustness against different gestures, speech patterns, or accents.

X. RESULTS AND DISCUSSION
COMPARISON ON ACCURACY

The ratio of correctly predicted observations to all observations is known as accuracy. (TP+TN) / (TP+FP+FN+TN) is the accuracy.

Table 1: Comparison Values of Accuracy

Number of Samples	Accuracy			
	Human Computer Interaction dataset			
	CNN	Enhanced CNN	LSTM	MLSTM
5	62.3	66.2	67.3	75.1
10	63.5	68.3	69.5	77.3
15	67.8	68.7	69.1	76.9
20	69.5	69	72.4	79.7
Average	65.8	68.05	69.6	77.3

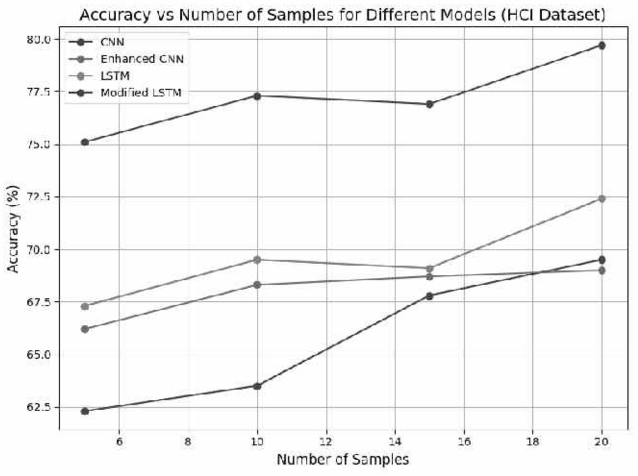


Figure 3. Simulation of Accuracy Summary of Table 1:

Comparison Values of Accuracy: The table compares the accuracy of four models - CNN, Enhanced CNN, LSTM, and MLSTM - on the Human Computer Interaction dataset using different sample sizes (5, 10, 15, and 20).

Overall Performance:

The MLSTM model consistently outperforms all other models across all sample sizes. Accuracy increases as the number of samples increases for all models, indicating better learning with more data.

Different Methodology Comparison :

CNN shows the lowest performance with an average accuracy of 65.8%.Enhanced CNN improves slightly to 68.05%.LSTM performs better with 69.6% average accuracy. MLSTM achieves the highest accuracy of 77.3%, showing a significant improvement over other models. The MLSTM model demonstrates superior accuracy and scalability, making it the most effective architecture for the Human Computer Interaction dataset among the compared models.

Precision comparison

Precision is the measure of how many of the positive predictions made by the model were actually correct.

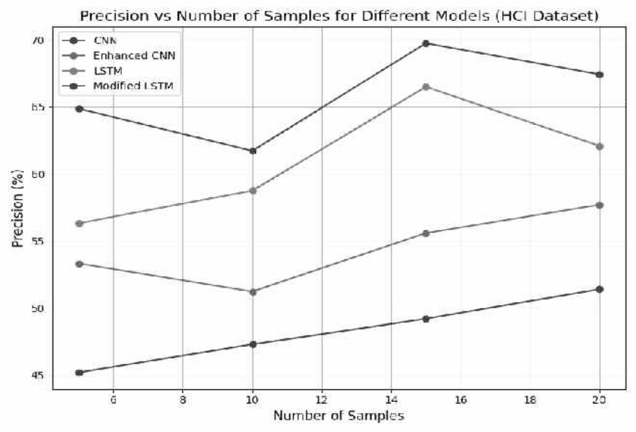
Precision = TP/TP+FP

Table 2: Values of Precision Comparison

Number of Samples	Precision			
	Human Computer Interaction dataset			
	CNN	Enhanced CNN	LSTM	MLSTM
5	45.2	53.33	56.33	64.88
10	47.3	51.23	58.75	61.73
15	49.2	55.6	66.5	69.75
20	51.4	57.7	62.1	67.43
Average	48.3	54.5	60.9	65.9

Figure 4. Simulation of Precision

Summary of Table 2 Precision Comparison: The study compares four models- CNN, Enhanced CNN, LSTM, and



MLSTM - on the Human-Computer Interaction dataset across varying sample sizes (5, 10, 15, 20).Precision improves consistently as the number of samples increases for all models. Among all models, MLSTM achieves the highest precision across all sample sizes.CNN shows the lowest precision, while Enhanced CNN and LSTM provide moderate improvements. The average precision values indicate the overall ranking: MLSTM (65.9%) > LSTM (60.9%) > Enhanced CNN (54.5%) > CNN (48.3%).The MLSTM model outperforms* all others in terms of precision, demonstrating its superior capability in handling the Human-Computer Interaction dataset.

Recall Comparison

Recall refers to the proportion of correctly predicted positive observations out of all the actual positive ones.

Recall = TP/TP+FN

Table 3: Values of Recall Comparison

Number of Samples	Recall			
	Human Computer Interaction dataset			
	CNN	Enhanced CNN	LSTM	MLSTM
5	57.3	65.9	71.3	73.4
10	58.7	61.5	76.1	78.6
15	55.6	64.4	74.8	77.3
20	53.4	62.3	73.2	76.2
Average	56.3	63.5	73.9	76.4

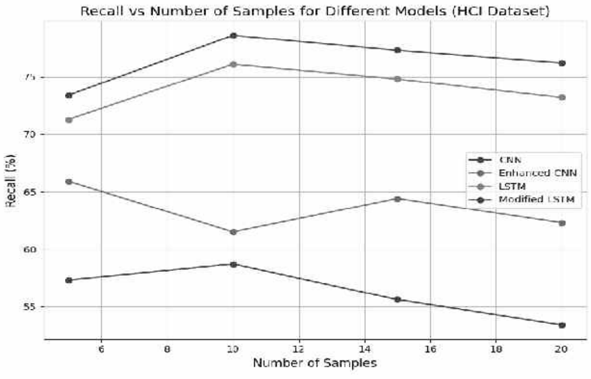


Figure 5: Simulation of Recall

Summary of Table 3: Recall Comparison : The table presents the recall performance of four models - CNN, Enhanced CNN, LSTM, and MLSTM - on the Human-Computer Interaction dataset across varying numbers of samples (5, 10, 15, and 20).MLSTM consistently achieved the highest recall across all sample sizes, indicating its superior ability to correctly identify relevant instances. LSTM also performed strongly, ranking second in recall across all cases. Enhanced CNN showed moderate improvement over the basic CNN model.

CNN had the lowest recall values in every test scenario.Average recall values:

CNN: 56.3%, Enhanced CNN: 63.5%, LSTM: 73.9%, MLSTM:76.4%.The MLSTM model demonstrates the best recall performance, followed by LSTM, indicating that memory-based models (LSTM and MLSTM) are more effective in capturing relevant patterns in the dataset compared to convolution-based models (CNN and Enhanced CNN).

F-Measure Comparison

The F-Measure is a metric that combines the balance between Precision and Recall, giving them a weighted score. This includes both false positives and false negatives. Unlike accuracy, F1 has an uneven distribution of classes. Precision and recall are better, but false positives and false negatives have different costs.

2*(Recall * Precision) / (Recall + Precision) is the F1 Score.

Table 4: Values of F-Measure Comparison

Number of Samples	F-Measure			
	Human Computer Interaction dataset			
	CNN	Enhanced CNN	LSTM	MLSTM
5	55.2	66.7	75.3	81.1
10	54.2	65.7	73.6	84.3
15	63.7	64.4	76.8	83.2
20	60.4	67.1	72.2	87.6
Average	58.4	65.9	74.5	84.1

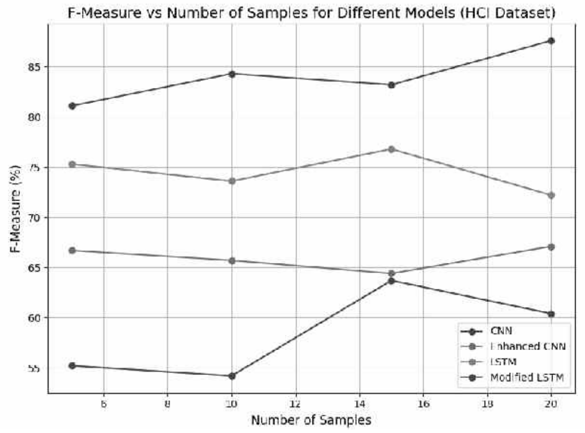


Figure 6: Simulation of F-Measure

Summary of Table 4: F-Measure Comparison: The table compares the F-Measure performance of four models — CNN, Enhanced CNN, LSTM, and MLSTM - across varying sample sizes (5, 10, 15, and 20).The MLSTM model consistently achieves the highest F-Measure across all sample sizes, indicating superior performance in balancing precision and recall.The CNN shows the lowest scores throughout, while the Enhanced CNN and LSTM provide moderate improvements.CNN: Average F-Measure = 58.4% - baseline performance. Enhanced CNN: Average F-Measure = 65.9% - moderate improvement over CNN. LSTM: Average F-Measure = 74.5% - significant gain due to sequential learning capability. MLSTM: Average F-Measure = 84.1% - best performer, showing the most accurate and stable results across all samples. The MLSTM outperforms other models by a margin of about 9.6% over LSTM and 18.2% over Enhanced CNN, confirming that the multi-layer LSTM architecture enhances classification accuracy for human–computer interaction data.

XI. CONCLUSION

The comparison of four models-CNN, Enhanced CNN, LSTM, and MLSTM-on the Human-Computer Interaction dataset reveals clear differences in performance across various metrics (accuracy, precision, recall, and F-Measure) and sample sizes (5, 10, 15, 20).

The MLSTM model consistently outperforms all other models across all metrics, demonstrating its superior accuracy, precision, recall, and F-Measure. The multi-layer architecture of MLSTM proves particularly effective for the Human-Computer Interaction dataset, surpassing both convolution-based models (CNN, Enhanced CNN) and sequential models (LSTM). MLSTM's exceptional performance makes it the most effective and scalable architecture for this task.

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