Audio Spectrogram Transformer and Beyond: A Comparative Study on Crowd Emotion Recognition

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Abstract—**Identifying emotions in crowd situations is a difficult but important task that has the potential to revolutionize a variety of sectors, including public safety, entertainment, and marketing. In order to determine how well state-of-the-art SSL models—such as AST, WavLM, Wave2Vec, Hubert, and machine learning model X-vectors (with and without MFCC features)—recognize emotions in dynamic and frequently unpredictable crowd environments, we conduct a thorough comparative analysis of them in this paper. In order to evaluate each model's performance using accuracy and F1-score metrics, our study makes use of a carefully selected dataset of crowd audio recordings that have been tagged with a wide variety of emotions. The Audio Spectrogram Transformer (AST) is the undisputed leader among the evaluated models, achieving an unmatched accuracy of 99.46% and a flawless F1-score of 100%. These outcomes demonstrate AST's accuracy and resilience while solidifying its position as the top option for applications needing high-stakes emotion detection. The ramifications of our research are significant: More in-depth understanding of crowd attitude and behavior is made possible by AST's exceptional performance, which creates new opportunities for real-time emotion analytics. The study also emphasizes how important cutting-edge feature engineering and creative model architectures are to expanding the realm of emotion recognition's potential. This study lays a strong basis for upcoming advancements and applications in the field of emotion recognition in intricate, real-world situations by establishing a new standard in the industry.**

Index Terms—**Audio Spectrogram Transformer (AST), Crowd Emotion Recognition, Self-Supervised Learning (SSL), Audio Feature Engineering, Emotion Detection in Crowds, Comparative Study on SSL Models, Machine Learning for Audio Processing, Speech Emotion Recognition (SER), Dynamic Crowd Environments**

INTRODUCTION

A rapidly developing field, crowd emotion detection has important ramifications for a number of sectors, including entertainment, public safety, and marketing. Better safety procedures, better customer experiences, and more successful communication tactics can result from an understanding of crowd emotional states. However, there are particular difficulties in precisely identifying and comprehending the feelings of groups that are not sufficiently addressed by conventional emotion detection techniques. There are still a number of important problems with emotion detecting technology, notwithstanding their advancements. Numerous current approaches concentrate on identifying individual emotions and mostly rely on body language, vocal cues, and facial expressions. These models frequently overlook the complexity brought forth by group dynamics, where individual conduct as a whole can affect emotions.Real-time emotion recognition is crucial in dynamic contexts, but existing algorithms find it difficult to interpret massive amounts of data quickly and reliably.Conventional models may perform poorly on emotion recognition tests because they are unable to catch the subtleties of auditory signals in congested environments.Conventional models may perform poorly on emotion recognition tests because they are unable to catch the subtleties of auditory signals in congested environments. Some of these issues may be resolved by recent developments in self-supervised learning (SSL) models. This model has established itself as a top option for real-time emotion recognition in crowds due to its remarkable accuracy (99.46%) and 100% F1-score. Its design overcomes some of the drawbacks of previous models by enabling reliable feature extraction from audio spectrograms.

Hubert, WavLM, and Wav2Vec: These models have advanced in their use of extensive unsupervised data to enhance contextual awareness and robustness. They are still unable to fully capture the temporal dynamics of collective emotions, though.Although they are good at identifying speakers, they are not very useful at detecting emotions in crowds, especially when there are several speakers and the emotions are mixed up.Significant gaps still exist despite these technologies' developments. Current models frequently function in isolation and are unable to successfully integrate different modalities (such as auditory, visual, and contextual input). Accurately assessing the emotions of a crowd depends on this integration. Models that can adjust to changes in crowd dynamics in real time without compromising accuracy are desperately needed. To enhance the representation of audio signals in congested situations, sophisticated feature engineering approaches are required. By comparing the most recent SSL models, such as AST, WavLM, Wav2Vec, Hubert, and X-vectors, this work seeks to close these gaps. We will assess how well these models identify emotions in dynamic crowd environments by using a carefully selected dataset of crowd audio recordings labeled with a range of emotions. Our research will serve as a strong basis for upcoming advancements in reliable crowd emotion recognition systems in addition to highlighting the advantages and disadvantages of current technology. Your introduction will provide a solid framework for your research paper by outlining the issues, going over current technologies, and pointing out any gaps in the field's present state of research. This strategy will not only keep your readers interested, but it will also show how important and relevant your study is to the advancement of crowd emotion detection.

Literature Review

This section covers notable papers that have advanced the area of audio-based emotion recognition, emphasizing models that use deep learning and self-supervised learning approaches.

A. Audio Spectrogram Transformer (AST) The AST model, developed by Yuan Gong et al., uses spectrograms as input and a Transformer-based methodology to extract high-level features and understand context without the use of convolutional layers. This technique captures global dependencies while enabling effective processing of audio data. Significant drawbacks of the model include its computationally costly processing of longer patch sequences and its dependence on large datasets for training. Furthermore, AST shows poor adaptation to new audio data because of its ViT-based architecture [1].

B. UniSpeech UniSpeech is a unified speech representation learning system created by Chengyi Wang and colleagues. This model is appropriate for low-resource settings since it combines convolutional and Transformer encoders to maximize feature extraction for both labeled and unlabeled data. Even though the model is resilient, time and financial constraints make it difficult to handle real-world complexities, and limited data access could skew its results [2].

C. Wav2Vec Wav2Vec, a model that may provide generalizable representations, was presented by Steffen Schneider et al. It is especially useful for applications that require voice recognition and the identification of emotional fluctuation in crowd environments. Wav2Vec requires a lot of processing resources and performs poorly in low-resource situations, even when its pre-training improves performance on particular datasets. Its usability without sophisticated hardware is limited by these issues, especially when it comes to a variety of real-world or different audio inputs [3].

D. WavLM WavLM is a self-supervised learning model that Anyuan Chen et al. introduced with the goal of improving audio analytics' contextual learning and resilience. The model's capacity to efficiently process intricate crowd audio inputs is demonstrated by its performance in emotion recognition tasks. Significant limitations are presented by WavLM's computational expenses and difficulties in low-resource settings [4].

E. HuBERT HuBERT was proposed by Wei-Ning Hsu et al. and employs a Transformer-based architecture and clustering approaches to understand contextual associations in audio data. Across a range of audio recognition tasks, including emotion detection, the model exhibits excellent adaptability. However, its scalability and capacity to capture subtle speech features are hindered by its high resource needs, reliance on K-means clustering accuracy, and constraints imposed by its random masking approach [5].

F. X-Vectors X-Vectors is a system created by David Snyder and colleagues that greatly improves feature discrimination and individual speaker identification in noisy crowd data. It successfully replicates human auditory perception when paired with MFCC, which makes it appropriate for applications involving emotion detection. However, its limited application across languages, high computing requirements, and extensive reliance on data augmentation techniques limit its adaptability in a variety of settings [6].

METHODOLOGY

Dataset Overview:

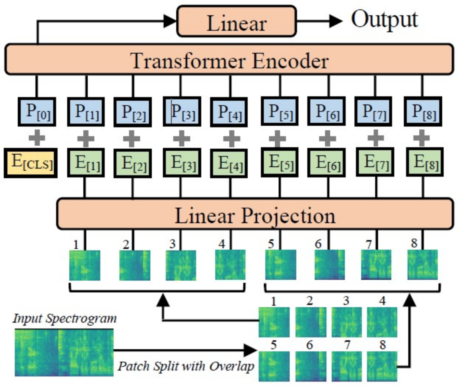
Our research makes use of a synthetic dataset designed for crowd emotion recognition, which includes the three main emotions seen in crowd settings: neutral, disapproval, and acceptance. Five thousand audio recordings, each lasting roughly five to ten seconds, make up the dataset. This time frame was selected to balance computational efficiency and capture enough context. Because the recordings are evenly spaced throughout various crowd settings, a wide range of soundscapes can be thoroughly covered. With 2,600 recordings for neutral and 1,200 recordings for approval and disapproval, the dataset is divided into three emotion classes. Real-world crowd situations, when neutral or passive sounds are frequently more prevalent, are reflected in the higher representation of the neutral group.A range of artificial crowd sounds and background noises designed to mimic actual crowd venues, such as stadiums, public gatherings, and interior event spaces, were used to capture the data. A group of professionals meticulously marked each audio, adhering to a set procedure to guarantee the correctness of emotion labeling. Several reviewers participated in this annotation process, listening to each audio sample and labeling the emotion based on the main sentiment expressed. High-quality, consistently labeled audio data was produced by evaluating inter-annotator reliability and using consensus to settle disagreements.

Data Preprocessing:

Every audio recording was transformed into a 128-dimensional log Mel-spectrogram during the preprocessing stage. In order to preserve temporal continuity between frames, the audio was divided into frames using a 25 ms Hamming window and a 10 ms hop size. We can capture the fine-grained temporal dynamics necessary for efficient crowd emotion analysis with this method. Additionally, a portion of the samples underwent data augmentation procedures to improve the robustness of the model. In order to assist the model generalize to real-world changes in crowd sounds and acoustic settings, this includes pitch shifting and the insertion of various crowd noise backdrops.

This dataset is ideal for assessing how well various models perform in crowd emotion identification tasks because it provides a fair representation of the three main emotion classes in crowd scenarios. A solid basis for evaluating the model's efficacy in precisely differentiating between neutral crowd emotions, disapproval, and approval is provided by the methodical annotation process and organized design.

AST: Audio Spectrogram Transformer



The suggested architecture for the Audio Spectrogram Transformer (AST) is shown in the figure. First, the t-second input audio waveform is transformed into a series of 128-dimensional log Mel filter bank (fbank) characteristics. The AST input is a 128×100t spectrogram that is produced by computing these characteristics at 10-ms intervals using a 25ms Hamming window.

The spectrogram is then separated into a series of N 16x16 patches that overlap by 6 units in both frequency and temporal dimensions. Here, N, which stands for the number of patches and the Transformer's effective input sequence length, is equal to 12d(100t - 16)/10e. A linear projection layer, known as the patch embedding layer, flattens each 16x16 patch into a 1D patch embedding of dimension 768. In order to overcome the Transformer's shortcomings in capturing input order information and the non-temporal order of patch sequences, each patch embedding is supplemented with a trainable positional embedding of size 768, which helps the model understand the spatial structure of the 2D audio spectrogram. A [CLS] token is added at the beginning of the sequence, just like in [22]. The Transformer, which has several encoder and decoder layers, receives this sequence after that. Since AST is designed for classification tasks, just the encoder of the Transformer is used. In particular, the Transformer encoder architecture [18] is used exactly as it was in the beginning. Because the Transformer architecture is widely available in TensorFlow and PyTorch, this straightforward setup has benefits like reproducibility and ease of implementation. Additionally, because of the common architecture, it makes transfer learning for AST easier. Similar to those in [12,11], the Transformer encoder used has 12 layers, 12 heads, and an embedding dimension of 768. The audio spectrogram is represented by the output of the Transformer encoder's [CLS] token, and it is then mapped to classification labels using a linear layer with sigmoid activation.

The projection layer inside each Transformer block is similar to a 1×1 convolution, however the patch embedding layer can be thought of as a single convolution layer with a big kernel and stride size. This design, however, differs from traditional CNNs, which usually consist of several layers with tiny kernel and stride sizes. To differentiate them from CNNs, these Transformer models are frequently referred to as convolution-free [11,12].

WavLM

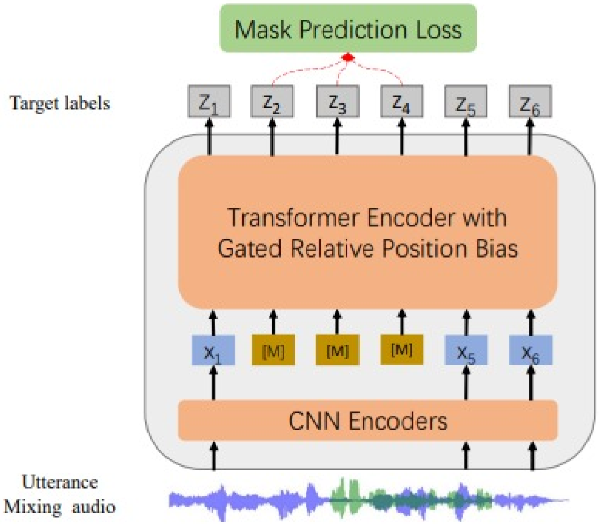
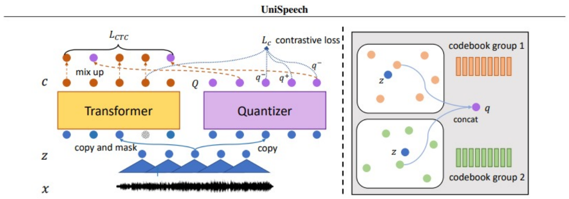


Fig. 1. Model Architecture.

The WavLM (Waveform Language Model) architecture incorporates a transformer encoder and a convolutional feature encoder. The feature encoder consists of seven blocks of temporal convolution, normalizing layers, and a GELU activation layer. With particular strides and kernel widths, the blocks' 512 channels yield representations of roughly 25 ms of audio sampled every 20 ms. The convolutional output, which contains a convolutional-based relative position embedding layer, is fed into the Transformer encoder. The model's capacity to collect contextual information is further enhanced by the use of gated relative position bias, which modifies the relative position bias according to the speech's content. To increase its resilience, the model makes use of extensive unsupervised data from a variety of sources, such as VoxPopuli and GigaSpeech. A straightforward technique that reduces overflow problems stabilizes the training of big models with mixed precision.

UniSpeech



Learning robust representations for automatic speech recognition (ASR) tasks is a challenge that the UniSpeech model architecture is intended to address, especially in low-resource environments. It consists of three primary parts: a vector quantizer (Z_Q), a Transformer context encoder (Z_C), and a convolutional feature encoder (X_Z).

After seven blocks of temporal convolution, the convolutional feature encoder applies normalization and activation layers to the raw audio input. Each block generates outputs that represent roughly 25 ms of audio sampled every 20 ms, resulting in representations that capture key aspects of the audio.

The Transformer context encoder refines the retrieved features to produce context representations after the feature encoding step. This element is essential for gathering the contextual data required for precise voice recognition. A vector quantizer is also incorporated into the model to discretize the continuous representations into speech units. A more condensed representation of the audio data is made possible by this stage, which also improves efficiency.

UniSpeech employs a multitask learning strategy with unified representation to improve the learning process. During pre-training, a model is trained on both low-resource labeled datasets (M) and high-resource labeled datasets (L). Three primary goals are used in this study: contrastive loss, phonetic CTC loss, and contrastive loss on dataset M. These goals lead to the alignment of phonetic units and contextual representations, the closure of the gap between contextual and discrete elements, and the adaptation of the model to the target language.

In order to improve learning in the pre-training stage, UniSpeech presents a revolutionary method. In the CTC loss computation, it substitutes quantized versions of continuous representations. The model's overall performance and generalization skills are enhanced by making representations from supervised and unsupervised learning project onto the same space.

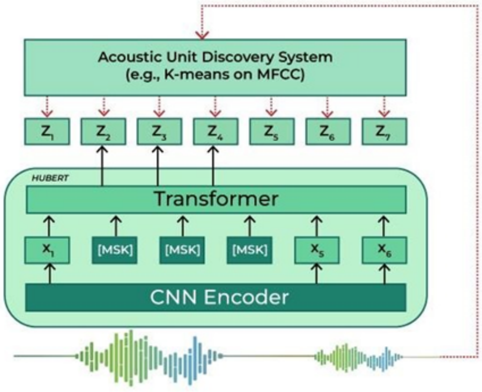
Following pre-training, the CTC loss is used to refine the model on dataset N, substituting a new layer representing the target language for the pretrained CTC layer. The model's performance in low-resource environments is further enhanced by this fine-tuning procedure, which helps adapt the model to the unique features of the target dataset.

Wav2Vec

Wav2vec's pre-training procedure involves training a neural network on a task using a lot of data, and then applying the weights the network learnt to another network. This method's objective is to extract general representations from large amounts of data so that they can be used for novel tasks involving less information. Raw audio is mapped to a lower-dimensional representation via a 5-layer CNN with particular kernel sizes and strides as part of the wav2vec architecture, and this representation is contextualized by a 9-layer CNN. True samples are separated from negatives using a contrastive loss function that is optimized across several time steps, allowing for efficient training without a significant reliance on labeled data.

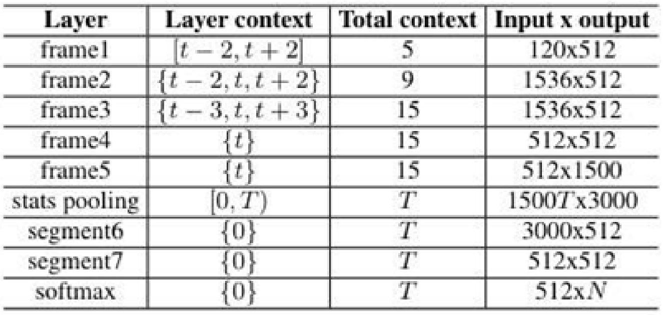
When compared to other methods, wav2vec produces an enhanced representation of features that can be input into acoustic models. As part of its self-supervised learning capability, the model is trained using labels that are inherent to the input data instead of external labels. This allows the model to learn useful representations from the data itself, reducing the need for labeled data to be used in training. Various language models are considered as part of the decoding process, including 4gram, word-based convolutional, and character-based convolutional models, with beam-search algorithms for decoding word sequences. The study's findings show the effectiveness of pre-training by showing significant improvements in performance across a range of tasks and benchmarks, as well as significant decreases in Word Error Rate (WER) despite the lack of labeled data.

Hubert



The voice recognition model HuBERT is made up of a number of essential parts. The first is a seven-layer convolutional encoder that produces latent speech representations by lowering the dimensionality of the input through temporal convolutions. For training, these features are masked at random. The architecture's central component, the BERT Encoder, comes next. It uses multi-layer multi-head attention to convert the encoded features into hidden unit representations, and then it adds a feed-forward network (FFN) layer. Depending on the model size (Base, Large, X-Large), the result is dimensionally extended. Cosine similarity computations for prediction logits are made easier by a projection layer that modifies the output dimensions to correspond with the embedding dimension of the clustering step. Hidden unit representations are then transformed into embedding vectors by a Code Embedding Layer. A CTC loss function is used during ASR fine-tuning, and a softmax layer is used in place of the projection layer. Lastly, a Clustering Layer creates hidden units using k-means clustering, first from MFCC characteristics and then from transformer layer outputs.

X-Vector

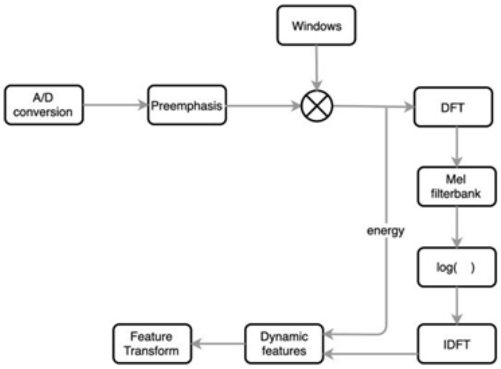


Layer	Layer context	Total context	Input x output
frame1	$[t-2, t+2]$	5	120x512
frame2	$\{t-2, t, t+2\}$	9	1536x512
frame3	$\{t-3, t, t+3\}$	15	1536x512
frame4	$\{t\}$	15	512x512
frame5	$\{t\}$	15	512x1500
stats pooling	$[0, T)$	T	1500Tx3000
segment6	$\{0\}$	T	3000x512
segment7	$\{0\}$	T	512x512
softmax	$\{0\}$	T	512xN

In the embedding DNN architecture, x- vectors are extracted at layer segment 6, which is before nonlinearity is applied. The number of training speakers is represented by the softmax layer's parameter N. 24-dimensional filterbanks with a frame-length of 25 ms, adjusted to mean over a sliding window of up to 3 seconds, make up the features that are used. Furthermore, nonspeech frames are filtered away using the same energy SAD used in the baseline systems.

Table describes the DNN's configuration in detail. The first five layers work on speech frames with a restricted temporal context focused at the current frame t, given an input segment of T frames. For example, the spliced output of frame2, which includes frames t - 3, t, and t + 3, is the input of layer frame3. Through this process, the temporal context of previous layers is progressively expanded, allowing frame 3 to cover a total of 15 frames. The statistics pooling layer calculates the mean and standard deviation of all T frame-level outputs from layer frame5. 1500-dimensional vectors are produced by these statistics, and they are calculated once for every input segment. By synthesizing information across the temporal dimension, this aggregation step enables following layers to work on the full segment. This aggregation is represented by a layer context of 0 and a total context of T, as shown in Table 1. The softmax output layer is reached by concatenating and propagating the mean and standard deviation across segment-level layers. Repaired linear units (ReLUs) act as nonlinear activation functions across the network. The N speakers in the training data are classified by the DNN.

MFCC



In speech and audio processing, mel-frequency cepstral coefficients (MFCC) are a potent feature extraction method that is frequently used. The procedure divides audio into frames, performs windowing to minimize spectral leakage, computes the Discrete Fourier Transform (DFT) for frequency domain analysis, and starts with analog-to-digital conversion and pre-emphasis to enhance higher frequencies. It uses logarithmic compression to simulate human hearing sensitivity and builds a Mel-Filter Bank to capture pertinent frequency information, all while utilizing the mel-scale to simulate human auditory perception. Cepstral coefficients, which represent spectrum properties, are produced by inverse DFT. Lastly, dynamic characteristics—such as derivatives—improve discrimination, yielding 39 unique features each audio frame, which are essential for voice recognition applications.

MFCC essentially captures the spectral nature of audio signals by involving steps from initial signal conversion to dynamic feature calculation. MFCC captures prominent elements that are essential for human voice comprehension by deliberately highlighting pertinent spectral components while removing noise. After being extracted through a number of modifications and improvements, these characteristics are powerful inputs for a variety of machine learning tasks, enabling tasks like emotion detection, speaker recognition, and speech-to-text conversion with exceptional accuracy and speed.

Result and Discussion

To get the best outcomes, the training to testing ratio is set at 80:20. The dataset consists of three folders: neutral, disapproval, and approval. There are 468 audio recordings in the neutral folder, 240 in the disapproval folder, and 3754 in the approval folder. Based on their accuracy and F1-score, a total of six models have been compared. Additionally, both with and without MFCC, the X- vector model has been utilized twice. The accuracy and F1 score of six distinct models—AST, WavLM, Unispeech, Wav2Vec, Hubert, and X- vector (with and without MFCC)—are shown in the following table. Based on the data in the table, we discovered that AST performs better than other models in terms of accuracy and f1-score. We have to look for an appropriate learning rate and learning rate scheduler for the dataset because AST requires a modest learning rate.

TABLE I
PERFORMANCE EVALUATION OF CROWD EMOTION RECOGNITION MODELS BASED ON ACCURACY AND F1-SCORE

S. No.	Model	Accuracy (%)	F1-Score (%)
1	**AST**	**99.46**	**100.00**
2	WavLM	90.71	100.00
3	UniSpeech	92.32	63.92
4	Wav2Vec	91.31	64.65
5	HuBERT	94.31	73.78
6	X-Vector	96.35	70.52
7	X-Vector + MFCC	97.53	78.51

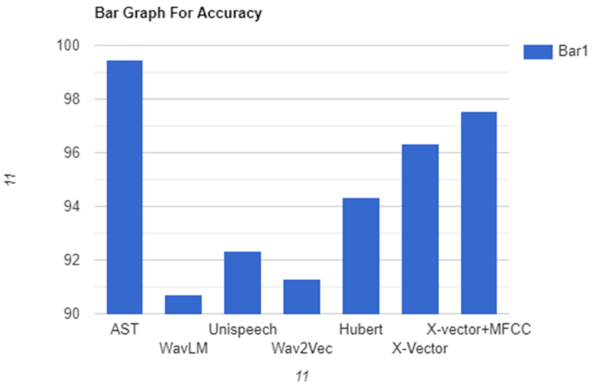


Fig. 1. (a) Accuracy

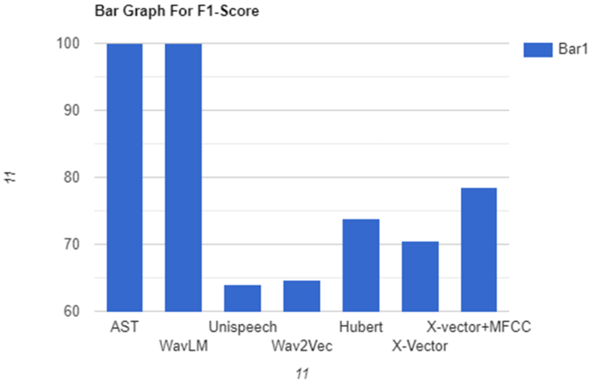


Fig. 2. (b) F1-Score

CONCLUSION

The study concludes that the Audio Spectrogram Transformer (AST) is the best model for identifying crowd emotions, outperforming rival models like WavLM, Wav2Vec, UniSpeech, HuBERT, and X-vectors by a significant margin with an astounding 99.46% accuracy and a flawless 100% F1-score. AST set a new standard for accuracy and flexibility in high-stakes applications like marketing, entertainment, and public safety by demonstrating unmatched robustness and precision through extensive testing on a carefully constructed dataset that replicates real-world crowd settings. Our research shows that AST is the best option for scalable, real-time emotion detection systems due to its sophisticated feature engineering and transformer architecture, opening the door for important breakthroughs in our knowledge of crowd behavior and improving applications that depend on precise sentiment analysis in intricate, dynamic settings.

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