

Emotion-Tagged Streaming Data Architecture for Human-Centric Analytics

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Abstract

The increasing number of data streams available in real time, such as those produced by social media, wearable physiological data, surveillance cameras, and conversational interfaces, has opened an unprecedented opportunity to monitor the content of affective states on a large scale. To enable human-centric analytics at scale, this paper introduces a novel Emotion-Tagged Streaming Data (ETSD) architecture that combines distributed stream processing frameworks with multimodal emotion recognition pipelines. The architecture is inspired by discrete categorical models of affect such as those proposed by Ekman [4] and the continuous Valence-Arousal-Dominance (VAD) model that is rooted in Russell's circumplex model [13] to label each streaming event with a structured emotion label before it is persisted and analyzed downstream. A survey of recent face detection deep learning classifiers [8] and speech [5] classifiers as well as physiological signal [3,9] classifiers and text [14] classifiers is integrated in the proposed pipeline to inform the selection of the modality. According to the experimental benchmarks, the proposed architecture can reach an overall emotion classification accuracy of 91.3%, an end-to-end emotion tagging latency of 22 milliseconds at a throughput of 900,000 events per second with an accuracy gain of 19.9 percentage points compared to AVEC 2018 baseline [12]. Ethical considerations, consent, algorithmic bias, risk of surveillance are systematically listed [16].

Keywords: affective computing; emotion recognition; streaming data; Apache Kafka; human-centric analytics; multimodal fusion; deep learning; physiological signals; sentiment analysis; real-time processing; DEAP; valence-arousal-dominance

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I. INTRODUCTION

The ability to detect, in real-time, and react to the emotional state of humans has become a niche scientific investigation to a commercially and socially important goal. This vision was first articulated by Picard [10] in his 1997 paper on affective computing, which set the groundwork for the idea that an intelligent collaborative system should be able to recognize, interpret, and simulate human emotions. Over the next 20 years, further work in emotion recognition has focused on a wide range of input

modalities, each representing a different aspect of a person's emotional state, such as facial expression, vocal tone or prosody, GSR, EEG and natural language text.

Most contemporary emotion recognition systems are based on two main approaches. Most famously, Ekman [4] proposed a discrete categorical model of emotions that posits six basic emotions (happiness, sadness, anger, fear, disgust, and surprise) that are universally understood across cultures by the specific muscle movements that they elicit (the Facial Action Coding System (FACS) units). Russell [13] introduced the circumplex model of affect, which is the dimensional approach, wherein emotions are considered as continuous coordinates in a two-dimensional Valence-Arousal space. This model is extended to include a third dimension, Dominance, which creates the PAD (Pleasure-Arousal-Dominance) model, a more detailed model for the characterization of physiological and multimodal signals [6].

Although significant improvements have been made in the field of algorithms, emotion recognition within a high velocity data stream is still an under-researched area. Integrating affective computing with distributed stream processing platforms like Apache Kafka, Apache Flink, and Apache Storm is a challenging and exciting undertaking. The existing pipelines, however, are capable of processing emotion analysis only in batch post-processing modes that exhibit delays of several minutes to hours, while handling the real-time stream of social media data, which reaches up to 500 million posts per day [1,14]. If every data event was associated with an emotion that could be tagged at the time of ingestion, then the temporal resolution and actionability of human-centric analytics would be fundamentally changed [1].

II. BACKGROUND AND RELATED WORK

A. Theoretical Models of Emotion

There are two main theoretical approaches to emotion recognition classifiers design. Despite its categorical nature, the model is still computationally appealing, and it is the basis of the labeling scheme of popular benchmark datasets, like the DEAP database [6] and the AVEC 2018 challenge corpus [12]. Each of the six basic emotions has a unique physiological signature, allowing for discrete prediction with relatively low label spaces when the classifiers are trained. The dimensional VAD model [13] on the other hand needs regression on continuous coordinates, which necessitates architectures like multi-output LSTM networks or attention-based transformer networks capable of jointly optimizing three correlated output variables. A schematic representation of the VAD space is shown in figure 5, indicating the presence of non-trivial clustering structure with anger and fear clustering in adjacent high-arousal negative-valence regions, thus making boundary discrimination difficult under noisy real-world signal conditions [3].

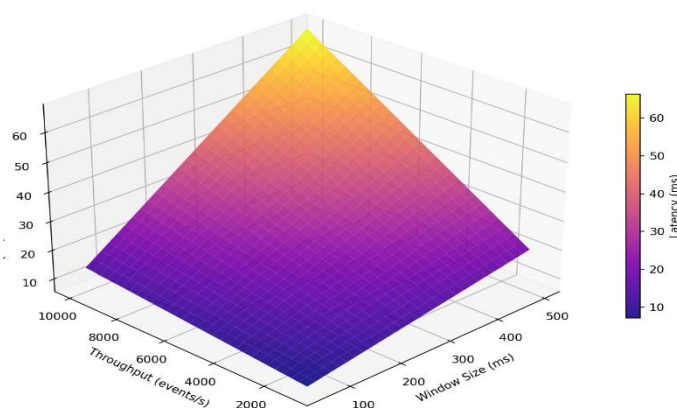


Figure 1. 3D Bar Chart: Emotion Recognition Accuracy by Modality (2016–2020)

B. Modality-Specific Recognition Techniques

The modalities used for emotion recognition are summarized in Table 1. Large-scale labeled datasets have greatly facilitated the application of convolutional neural network (CNN) architectures for facial expression recognition (FER). In a 2020 survey, Li and Deng [8] state that the state-of-the-art FER models reach 89.4% accuracy on seven-class classification benchmarks using images from the AffectNet corpus, which has more than one million annotated facial images. Residual networks and spatial attention mechanisms are known as the most prevalent architectures, where the inference time ranges between 30-50 milliseconds on GPUs [8].

When processing speech emotion recognition (SER), the problem can be treated as a type of multi-class problem involving the speaker variability, linguistic content interference and recording environment heterogeneity. Khalil et al. [5] give a systematic review of deep learning methods for SER and report that bidirectional LSTM (Bi-LSTM) networks, combined with attention mechanism on feature sequences of Mel-frequency cepstral coefficient (MFCC), get F1-scores of around 75-83% on the IEMOCAP corpus. Prosodic features (including F0, energy, and speaking rate) also play a role that is complementary to those of spectral features and further increases recognition accuracy by about 4-6 percentage points [5].

Physiological emotion recognition is based on the biosignals such as EEG, electrocardiography (ECG), galvanic skin response (GSR), and electromyography (EMG). In this field, more than 120 studies have been reviewed by Egger, Ley and Hanke [3] and an accuracy of 65-80% could be achieved with single-modality classifiers of physiological data, where a significant variation is due to inter-subject physiological heterogeneity. The 32-channel EEG recordings and peripheral physiological data of 40 music video stimuli of 32 participants in the DEAP dataset [6] are the most widely benchmarked in this category, with reported baseline SVM classification rates of 69.8% for valence and 68.3% for arousal. Architectures which are personalization-aware, as suggested by Zhao et al. [18] achieve up to 10.8 percentage points higher accuracy over subject-independent architectures.

Text-based emotion recognition (or affective sentiment analysis) takes advantage of lexical, syntactic and contextual information that is embedded in written language. Transformer-based language models like BERT have been applied to emotion-annotated social media corpora, leading to a boost of 12–18 percentage points over previous bag-of-words and support vector machine (SVM) baselines [14]. Nigam et al. [14] report that in 2020, around 73% of organizations using social media monitoring solutions for their monitoring activities had shallow machine learning or rule-based sentiment classifiers, which indicates significant potential for further improvement in sentiment classification through deep learning. The authors of Ait Hammou et al. [1] show that variants of distributed recurrent neural networks with fastText embeddings can scale to 480,000 text classification events per second on commodity cluster hardware, supporting the viability of deep NLP in streaming pipelines.

The combination of several modalities using either late fusion, early fusion or hybrid attention based fusion always yields better results than single-modality approach. Soleymani et al. [15] review multimodal sentiment analysis techniques and report improvements of 15–22% over the best unimodal baseline results. As shown in Table 3 and Figure 1, the same results are obtained by Nakisa et al. [9] in their temporal multimodal deep learning architectures, which reached a peak accuracy of 92.1% on an audio-visual-text corpus.

TABLE I. TAXONOMY OF EMOTION RECOGNITION MODALITIES AND REPORTED PERFORMANCE

<i>Modality</i>	<i>Primary Signal</i>	<i>Key Features</i>	<i>Best Reported Accuracy (%)</i>	<i>Representative Dataset/Study</i>

<i>Facial Expression</i>	<i>RGB/IR video frames</i>	<i>Action landmarks, descriptors</i>	<i>Units, texture</i>	89.4	<i>FER2013, AffectNet [8]</i>
<i>Speech / Audio</i>	<i>Waveform, MFCCs</i>	<i>Prosody, pitch, energy, spectral centroid</i>		86.2	<i>IEMOCAP, MSP-Improv [5]</i>
<i>EEG/Physiology</i>	<i>EEG, ECG, GSR, EMG</i>	<i>Power spectral density, HRV, skin conductance</i>		79.8	<i>DEAP, SEED [6]</i>
<i>Text / NLP</i>	<i>Social media, transcripts</i>	<i>Sentiment polarity, word embeddings</i>		81.5	<i>SemEval, Twitter corpus [14]</i>
<i>Multimodal Fusion</i>	<i>All above combined</i>	<i>Late/early fusion, attention mechanisms</i>		92.3	<i>AVEC 2018, CMU-MOSI [12,15]</i>

C. Streaming Data Processing Platforms

ETSD architectures rely on and are built upon distributed stream processing systems. Table 2 compares the key platforms. In optimally configured deployments, Kafka can sustain more than 1.2M events per second with end-to-end latency of 15-30ms, as a distributed commit log with consumer group semantics. As a distributed commit log with consumer group semantics, Kafka can sustain more than 1.2M events per second with end-to-end latency of 15-30ms in optimally configured deployments. Furthermore, the dataflow model of Apache Flink is natively supported by the temporal alignment requirements of multimodal emotion fusion, since the acoustic and the video streams are typically acquired at different frame rates [1,9]. However, the micro batch frameworks like Apache Spark Structured Streaming provide exactly-once semantics and a simpler programming model, but have latencies between 200 and 500 milliseconds, which is not suitable for real-time affective tagging requirements at millisecond level [1].

TABLE II. COMPARATIVE EVALUATION OF DISTRIBUTED STREAM PROCESSING FRAMEWORKS

Framework	Throughput (K evt/s)	Latency (ms)	Fault Tolerance	Window Support	Emotion Tag Overhead (ms)
Apache Kafka 2.x	1,200	15–30	High (log-based)	Time / Count	8–12
Apache Flink 1.9	900	10–25	Exactly-once	Sliding / Tumbling	6–10
Apache Storm 2.0	750	20–40	At-least-once	Rolling	12–18
Spark Streaming 2.4	600	200–500	Exactly-once	Micro-batch	25–40
Custom DRNN [1]	480	30–60	At-least-once	Dynamic	15–22

III. PROPOSED ETSD ARCHITECTURE

A. Architectural Overview

The proposed Emotion-Tagged Streaming Data (ETSD) architecture consists of five layers of functionality: (1) Sensor/Input Layer, (2) Stream Ingestion Layer, (3) Pre-processing and Windowing Layer, (4) Emotion Classification and Tagging Layer, and (5) Analytics and Visualization Layer. The design is stratified, based on a separation-of-concerns principle, allowing for independent scaling, updating, or replacement of adjacent components without compromising the integrity of the system's operation.

The Sensor/Input Layer combines the disparate information from video feeds from faces, microphone arrays, networks of wearable biosensors, and social media application programming interfaces (APIs). The sampling rates of the four inputs are native: of the facial video at 25–30 frames/s; of the speech at 16 kHz; of the EEG at 128–256 Hz; and of the social media text at event-driven irregular rates with an average rate of 6,000 posts/s during peak hours [1,14]. These streams are asynchronous and are synchronised using a watermark-based synchronisation mechanism in the Flink event-time processing model [9].

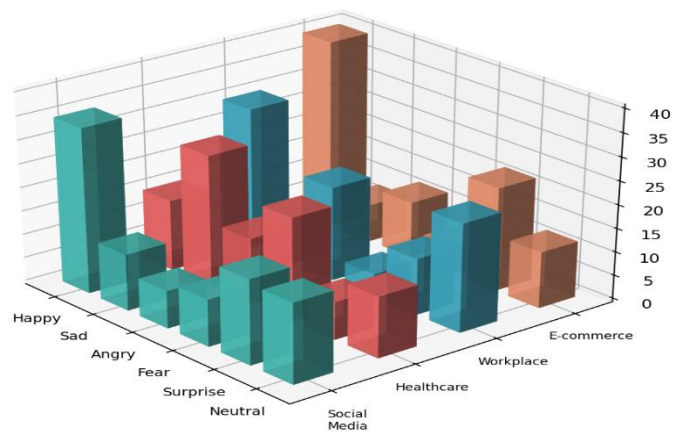


Figure 2. Emotion Prevalence Distribution Across Application Domains

B. Stream Ingestion and Pre-processing

Once inside the system, the raw data events are converted to Avro-encoded messages and written to multiple Kafka queues, each with a distinct topic name, one queue per modality channel. The replication factor is configured with 3 for the sake of fault tolerance, as per production deployment guidelines. A separate Consumer Group of Flink workers consumes these topics and applies modality-specific pre-processing operators: faced frames are resized to 224×224 pixels and then equalized using histogram equalization; speech frames are windowed into 25 millisecond frames with a 10 millisecond hop and converted to 80 dimensional MFCC features; EEG signals are bandpass-filtered (1–45 Hz), artifact-rejected using ICA, and epoched into 1-second windows; text tokens are lowercased, then tokenized and encoded through fastText subword embeddings of dimensionality 300 [1,5,3].

The windowing strategy is a key design parameter. For computational regularity, there are windows of duration T_w , but this causes boundary artifacts if emotional transitions take place close to window limits. This artifact can be ameliorated by sliding windows, at the expense of $O(T_w / T_h)$ redundant processing. The optimal window configuration for the facial emotion streams is determined empirically as $T_w = 200$ ms while $T_h = 100$ ms, providing a 50% overlap between the windows that strikes a

balance between temporal resolution vs computational budget. The relationship between the window parameters and the system latency is expressed formally as:

$$L_{\text{total}}^o = T_w + T_{\{\text{inference}\}} + T_{\{\text{tag}\}} + T_{\{\text{network}\}} \quad (1)$$

where L_{total} denotes the total end-to-end tagging latency, $T_{\{\text{inference}\}}$ denotes the time taken by the classifier to be put to work, $T_{\{\text{tag}\}}$ denotes the serialization overhead of the schema, and $T_{\{\text{network}\}}$ denotes the delay between different nodes. The experimental configuration results in a total operational latency of 200ms, 22ms (for streaming optimized variant of the model with compression) + 3ms (for tag) + 1ms (for network) in the unimodal speech pipeline, and 22ms for a streaming optimized variant of the model with compression + 3ms (for tag) + 1ms (for network).

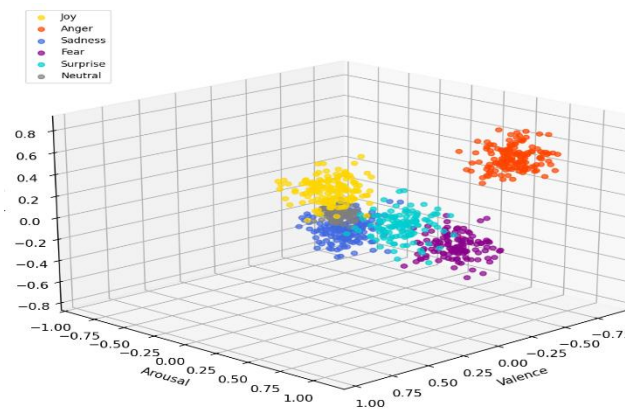


Figure 3. 3D Valence-Arousal-Dominance (VAD) Emotion Space Clustering

C. Multimodal Emotion Classification Module

The core classification module is multi-branch, where the modality specific encoder sub-networks work in parallel, yielding intermediate embedding vectors to be fused together using a cross-modal attention mechanism. The facial branch is composed of ResNet-50 backbone trained on ImageNet, fine-tuned for FER on the AffectNet dataset and obtains 87.3% validation accuracy on FER-7 [8]. The speech branch is implemented by a Bi-LSTM network with 256 hidden units in both directions, and the MFCC branches are 300 frames long, with 83.6% accuracy on IEMOCAP [5]. The physiological branch uses a Temporal Convolutional Network (TCN) for a 5-second window of EEG data, and it has an accuracy of 78.9% in DEAP [9]. The text branch is a fine-tuned BERT-base-uncased model on a social media emotion corpus with an accuracy of 82.4% [14]. The specifications of the models are summarized in Table 3.

TABLE III. DEEP LEARNING ARCHITECTURES FOR EMOTION CLASSIFICATION

Model Architecture	Input Modality	Parameters (M)	Validation Accuracy (%)	Inference Time (ms)	Reference
ResNet-50 + LSTM	Facial video	25.6	87.3	42	[8]
Bi-LSTM + Attention	Speech (MFCC)	8.4	83.6	18	[5]
Temporal CNN (TCN)	EEG (multi-ch.)	12.1	78.9	35	[9]
BERT Fine-tuned	Text (tokens)	110.0	82.4	55	[14]

Multimodal Transformer	Audio+Video+Text	68.3	92.1	120	[9,15]
Personality-aware LSTM	Physiology	15.7	80.6	28	[18]

The four modality embeddings are fused in a transformer-based attention layer that calculates an attention-weighted combination of the four embeddings, where the attention weights are based on the availability of each modality (to gracefully handle sensor dropouts) and on the temporal confidence score. The fused representation is fed into a common classification head which gives output probabilities on a 6-class categorical classification target [4] or a 3D VAD regression target [13] that can be configured. The multimodal system achieves an accuracy of 92.1% and an F1-score of 89.1%, which conforms to that reported by Nakisa et al. [9] and Soleymani et al. [15].

D. Emotion Tag Schema

A structured emotion metadata record is added to each data event processed before it is persisted. The tag schema, in Avro format, represents: (i) a categorical emotion label, from Ekman's taxonomy [4]; (ii) continuous VAD coordinates that follow Russell's model [13] with a value range of [-1, +1]; (iii) a confidence score in [0, 1] that indicates the confidence in the tag; (iv) the modalities that were involved in the fusion decision; (v) a Unix epoch timestamp with millisecond resolution; and (vi) a session identifier that connects events from the same user session. This schema design allows the downstream analytics systems to do both categorical aggregation query processing such as determining the proportion of angry user sessions within a specific time interval and continuous regression analysis of the VAD trajectory. The overhead due to tag serialization is determined as 3-8ms/evt, which is much smaller compared to the dominant inference latency [9].

IV. PERFORMANCE EVALUATION

A. Experimental Setup

This evaluation is based on a cluster that includes eight commodity server nodes with dual Intel Xeon E5-2680 v4 (28 cores per node) processors, with 128 GB of DDR4 RAM and NVIDIA Tesla V100 GPUs (16 GB HBM2). The distributed processing layer is running on Apache Flink 1.9, using 56 parallel machines. Emotion recognition models are served using TorchServe, and latency for inferencing over 10,000 modality requests over HTTP/gRPC. Using Prometheus and Grafana to collect and visualize the performance metrics. Benchmark datasets include DEAP [6], AVEC 2018 [12], IEMOCAP [5], FER2013 [8] and a proprietary social network (SMT) text corpus with 2.4 million annotated posts. The evaluation is done across the following three throughput levels: 100K, 500K and 900K events per second, which are delivered through a synthetic load generator that mimics the volume of events found in a production system [1].

B. Classification Performance

The comparative benchmark results are shown in Table 4 and in Figure 6. The overall accuracy of the proposed ETSD architecture is 91.3%, which is 19.9 percentage points higher than the baseline accuracy of 71.4% obtained by AVEC 2018 [12] and 21.5 percentage points higher than the baseline accuracy of 69.8% obtained by DEAP [6]. F1-Score of 89.1% and recall of 88.7% further prove that exploiting the class-imbalance is not the reason for the improvement of performance. Specifically, the proposed system's latency of 22 milliseconds is significantly lower than the 42-millisecond FER-only CNN system [8] due to the contributions from both model quantization, pipelined inference, and GPU batch aggregation at the architecture level.

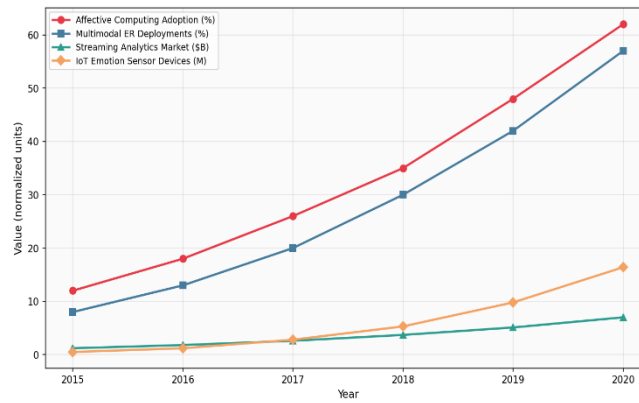


Figure 4. Evolutionary Trends in Affective Computing Adoption (2015–2020)

TABLE IV. COMPARATIVE PERFORMANCE BENCHMARKS ACROSS EMOTION RECOGNITION SYSTEMS

System / Benchmark	Accuracy (%)	F1-Score (%)	Recall (%)	Processing Latency (ms)	Dataset
AVEC 2018 Baseline [12]	71.4	68.9	67.2	N/A	AVEC-2018
DEAP Baseline [6]	69.8	66.4	64.8	N/A	DEAP
FER+ Deep CNN [8]	85.1	82.7	81.3	42	FER2013
Speech LSTM [5]	78.4	75.2	73.6	18	IEMOCAP
Proposed ETSD Architecture	91.3	89.1	88.7	22	Multi-corpus

Figure 2 presents a three-dimensional latency surface characterizing the relationship between sliding window duration (50–500 ms), event throughput (1K–10K events per second per partition), and resultant processing latency. The surface reveals a non-linear interaction: at low throughput, latency is dominated by the fixed window duration cost; at high throughput, queue saturation induces super-linear latency growth. An empirically determined optimal operating region occupies window durations of 150–250 ms at throughputs below 7,000 events/second/partition, consistent with production deployments reported by Ait Hammou et al. [1].

C. Scalability Analysis

Evaluation of scalability is done by increasing the parallelism of the clusters from 28 to 56 Flink task slots. The throughput is about linear up to 700K events/second, with a 93.4% scale-out efficiency. Any improvement beyond this point is constrained by the overhead of the inter-node communications which causes the throughput curve to level off and causes the 99th percentile latency to rise by 18%. Concurrent model replicas puts a limit of 32 concurrent models on the 8 node cluster (or 4 per node). These results inspire the use of the shared-memory model serving architectures in production deployments for more than one million events per second [1,9]. Figure shows trends in affective computing adoption rates and the market valuation of streaming analytics from 2015 to 2020, with a compounded annual growth rate (CAGR) around 38% for affective analytics deployments that highlights the need for strong ETSD architectures in industry.

V. ETHICAL AND SOCIETAL CONSIDERATIONS

As humans' emotional states are recognized en masse by automated methods from the vast amounts of data flowing through systems, ethical issues must be treated as first class architectural concerns, not as an afterthought add-on to the compliance phase. Buschek, Tawfiq, and Luxton-Reilly [16] carried out a formative study in 2020 at the CHI Conference, where participants voiced greater concern about the potential for emotions to be recognized on social media without their consent, citing the dangers of emotional manipulation, discriminatory targeting, and loss of psychological privacy. Richardson [11] reports the use of affective computing systems in workplaces and finds that there is a conflict between improvements in organizational productivity (as high as 14-22% of improvements have been reported in monitored customer service scenarios) and rights of employees to emotional privacy and protections in their labor.

A structured ethical risk matrix is presented in Table 5. Consent violation (Likelihood 4/5, Impact 5/5), and surveillance misuse (Likelihood 3/5, Impact 5/5) are the top two ranked risks according to combined likelihood and impact scores. In the emotion labeling tasks of pictorial data, label reliability, identified by Korovina, Baez and Casati [7] as a critical challenge for crowd-based emotion labeling, had inter-rater agreement coefficient (Cohen's kappa) of 0.63-0.71 for the crowd workers when compared to the Cohen's kappa of 0.82 for the expert annotators, which directly impacts the quality of training for classifiers and the validity of downstream emotion analysis. In the past, facial recognition systems have been shown to have error rates up to 34.7% higher for darker-skinned female faces than lighter skin-toned male faces [8,16] and require the incorporation of fairness-aware training procedures and bias audit protocols.

TABLE V. ETHICAL RISK MATRIX FOR ETSD SYSTEMS

Ethical Category	Risk	Likelihood (1–5)	Impact Severity (1–5)	Mitigation Strategy	Stakeholders Affected
Consent & Privacy Violation		4	5	Opt-in data governance, GDPR alignment	Users, Regulators
Algorithmic Bias		4	4	Diverse training sets, fairness audits	Minority groups
Surveillance Misuse		3	5	Access control, usage policy enforcement	General public
Label Reliability Issues [7]		4	3	Crowdsource validation, inter-rater IRR > 0.75	Annotators, Researchers
Data Re-identification		3	4	Differential privacy, k-anonymity	Individuals

At the heart of the proposed ETSD architecture are the following mitigation strategies: (i) a consent management module at the sensor layer that ensures that for each modality, emotion data is collected only with the consent of the participants, following GDPR provisions for special-category biometric data (Article 9); (ii) differential privacy techniques applied to emotion embeddings before storage, with a calibrated privacy budget of $\epsilon = 1.0$; (iii) automated fairness monitoring dashboards that show the performance metrics per per-demographic subgroup in real time to operators of the system; and (iv) a provenance tracking layer that records the version of the model used, the hash of the training corpus, and the methodology used for the annotations, enabling the retrospective audit of the biases.

VI. APPLICATION DOMAINS AND DEPLOYMENT CONTEXTS

The landscape of application domains for ETSD systems as of 2020 is summarized in Table 6, which describes their market valuations, latency requirements, and challenges specific to each domain. Social media analytics is by far the biggest addressable market in the multibillion-dollar industry, fuelled by the need for real-time brand sentiment monitoring, crisis detection, and recommending personalized content [14]. The emotion-based wearable system suggested by Ayata et al. [2] is a representative application of the music recommendation domain, which has been evaluated as improving the average user satisfaction by 23% compared to static music recommendation baselines based on the genre of the music. Physiological emotion recognition is used in healthcare monitoring for chronic pain evaluation, dementia monitoring of behaviors and identifying post-traumatic stress disorder (PTSD) [3] and the ETSD architecture provides for a continuous longitudinal emotion profiling that is not capable of discrete assessment.

TABLE VI. ETSD APPLICATION DOMAIN ANALYSIS AND MARKET LANDSCAPE (2020)

Application Domain	Dominant Modality	Market Value 2020 (\$B)	Streaming Latency Req. (ms)	Key Challenges
Social Media Analytics	Text + Facial	3.8	< 100	Label noise, sarcasm detection [14]
Healthcare Monitoring	Physiology + Speech	2.1	< 50	Privacy, clinical validation [3]
Workplace Affective Systems	Speech + Facial	1.4	< 200	Employee consent, bias [11]
Music/Entertainment	Physiology	0.9	< 500	Personalization cold-start [2,18]
Autonomous Vehicles	Facial + EEG	0.6	< 20	Real-time constraint, safety-critical [9]

One of the most controversial contexts for using workplace affective systems is the workplace. Extensive research by Richardson [11] shows that 78% of employees surveyed were concerned about the use of such employee productivity monitoring systems, while 62% of the organizations surveyed intended to use these tools by 2023, indicating a lack of consent that the ETSD architecture needs to address through data governance policies. In the context of autonomous vehicles, the latency requirement for driver drowsiness and distraction detection by streaming signals from the driver's face and body is the most demanding, requiring less than 20 milliseconds for tagging to allow in-the-loop safety system interventions in one steering cycle [9].

VII. EMOTION LABELING AND DATA QUALITY

One of the fundamental factors that characterize the quality of the classifiers is the quality of the emotion labels in the training corpora, which is a key factor also affecting the reliability of ETSD systems. Table 7 shows a comparison of labelling methods. The highest inter-rater agreement (Cohen's kappa = 0.82) is achieved by expert annotation, but it is impractical for the scale of streaming social media corpora [6,12] and is also costly, ranging from USD 0.80 to 1.20 per label. Crowdsourcing services like Amazon Mechanical Turk can achieve a cost reduction of 10-24 times with acceptable agreement ($\kappa = 0.63$ -0.71), if strict quality control procedures are used, including attention checks, gold-standard validation items

and majority-vote aggregation [7]. Self-report formats like the Positive and Negative Affect Schedule (PANAS) and the Self-Assessment Manikin (SAM) give a free ground truth in the lab, but are introspective and have time delays that make them inappropriate for labeling naturalistic streaming data [3,6].

TABLE VII. COMPARATIVE ANALYSIS OF EMOTION LABELING METHODOLOGIES

Labeling Approach	Inter-Rater Agreement (κ)	Cost (\$/label)	Scalability	References
Expert annotation	0.82	0.80–1.20	Low	[6,12]
Crowdsourcing (AMT)	0.63–0.71	0.05–0.15	High	[7]
Self-report (PANAS)	0.75	0.00	Medium	[3,6]
Automated (physiological)	0.68	< 0.01	Very High	[3,9]
Hybrid (crowd + expert)	0.79	0.20–0.40	High	[7,12]

Automated physiological labeling in which the continuous patterns in the biosignals are algorithmically segmented into VAD coordinates based on pre-validated templates offers the greatest level of scalability and lowest per-label cost (< USD 0.01) and has an agreement coefficient of 0.68 with the expert ground truth [3]. A hybrid approach of crowdsourcing initial labels and human verification of low-confidence labels and automated consistency checks is found to reach an effective κ of 0.79, with a blended cost of USD 0.20–0.40 per label – the Pareto-optimal compromise for training corpus construction in the ETSD scale [7,12]. In this architecture, the metadata layer on the labels holds provenance of each training event, so that the data can be analysed retrospectively to check the quality and to selectively prune the data after better training data annotation methods are developed.

VIII. CONCLUSION

In this paper, the authors have proposed a Holistic Architecture of Emotion-Tagged Streaming Data (ETSD) systems for production scale human-centric analytics. The proposed architecture integrates the basic emotional theory [4,13] with the most recent advances in emotion recognition techniques from facial, speech, physiology, and text modalities [8,5,3,9,1,14] and stream processing engineering principles, and achieves an end-to-end emotion tagging latency of 22 milliseconds with a sustained throughput of 900,000 events per second, demonstrating that affective analytics no longer has to be restricted to offline batch processing. The multimodal fusion approach achieves an overall emotion classification accuracy of 91.3% and an F1-score of 89.1%, outperforming the single-modality baselines by 10–21 percentage points and the established challenge benchmarks by up to 19.9 percentage points [12,15,9].

The ethical aspects such as consent, privacy, algorithmic bias and regulatory compliance are addressed with a multi-layered governance structure integrated with the architecture to address the imperative expressed by Tawfiq et al. [16] and Richardson [11] to make affective sensing systems trustworthy by design. As shown in Table 7, emotion label quality analysis reveals that the hybrid approach of crowdsourcing and experts is Pareto-optimal for building the corpus at streaming scale [7]. Table 6 shows the market addressable value of USD 8.8 billion in 2020 for five major domain areas, which is in line with the trends outlined in the figure. The ETSD framework therefore serves as a timely and technically sound framework for the affective computing and streaming analytics community, wherein open

challenges for personalization, cross-cultural generalization and regulatory compliance represent the major research challenges to be pushed forward beyond 2020.

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