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Transformer Architectures for Cat Vocalization Recognition

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ABSTRACT: *This paper presents a Transformer-based model for cat vocalization recognition, addressing the limitations of CNNs and RNNs in capturing long-range acoustic patterns. Our architecture combines multi-head self-attention with locality-enhanced convolutions to achieve 94.2% accuracy in emotion classification, outperforming traditional methods by 5.7%. The model processes Mel-spectrogram patches with dynamic positional encoding, with attention heatmaps revealing key frequency bands (e.g., 500-800Hz for pain detection). Optimized for edge deployment via 8-bit quantization and pruning, the system achieves <15ms latency on ESP32-S3 hardware. Applications include smart feeders (hunger detection), health monitoring (pain alerts), and human-cat interaction aids. This work demonstrates the potential of Transformers in animal communication analysis while maintaining practical deployability.*

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I. INTRODUCTION

Cats communicate through a rich repertoire of vocalizations that encode nuanced emotional states (e.g., pain, hunger) and behavioral intent. Existing methods relying on MFCC+CNNs fail to capturelong-term melodic patterns such as rising/falling pitch contours, which are critical for distinguishing between solicitation purrs and distress calls [1]. These limitations stem from the inherent locality of convolutional operations and the loss of temporal dependencies when using frame-level acoustic features [2]. Furthermore, contextual dependencies between vocalization segments—such as the transition from a high-frequency "isolation meow" to a low-frequency growl—are often overlooked by traditional spectral representations [3].

Recent studies in human speech emotion recognition (SER) highlight the shortcomings of static features like MFCCs, which struggle to encode dynamic prosodic cues (e.g., pitch variability, spectral flux) that are equally vital in cat vocalizations [4]. Hybrid approaches combining time-domain features with Mel-spectrograms have shown promise in SER by preserving transient acoustic events [5], yet their application to animal vocalizations remains underexplored. Cross-species research, such as WhisperSeg's adaptation for animal voice activity detection, demonstrates that Transformer architectures can generalize across taxa by modeling spectro-temporal patterns at varying timescales [6].

The lack of annotated bioacoustic datasets further complicates cat vocalization analysis. Self-supervised methods like AVES (Animal Vocalization Encoder) mitigate this by pretraining on unlabeled audio before fine-tuning for downstream tasks, achieving performance comparable to supervised models [7]. However, even state-of-the-art systems often ignore cross-modal correlations, such as the synchronization of meows with tail flicks or ear movements—a gap addressed by multimodal frameworks like Baidu's patented feline communication analyzer [8].

In edge deployment scenarios, computational constraints exacerbate these challenges. While quantized CNNs (e.g., SincNet) reduce latency by processing raw waveforms directly [9], they sacrifice the global receptive fields needed to classify extended vocal sequences [10]. Transformers offer a compelling alternative, leveraging self-attention to model long-range dependencies without heuristic feature engineering [11]. Their interpretability, via attention heatmaps, aligns with veterinary needs for explainable AI in pain detection [12]. Ethical concerns—such as overreliance on automated interpretation—are also emerging, necessitating guidelines akin to those proposed for SER in human-robot interaction [13].

This paper bridges these gaps by introducing a Transformer-based framework optimized for edge devices, advancing beyond MFCC+CNN baselines while addressing scalability, interpretability, and multimodal integration. Our work builds on bioacoustic precedents like AST (Audio Spectrogram Transformer) [14], adapting its strengths to the unique demands of feline vocal classification.

II. Proposed Architecture

The proposed architecture is designed to address the unique challenges of cat vocalization recognition through a carefully optimized Transformer-based approach. Unlike traditional methods that rely on frame-level processing, our system employs a hierarchical feature extraction strategy that preserves both local acoustic details and global temporal patterns. This is particularly crucial for analyzing feline vocalizations, which often contain rapid frequency modulations and subtle harmonic structures that convey emotional states and behavioral intent.

The architecture consists of three primary components working in tandem: an advanced input representation layer that transforms raw audio into optimized spectral patches, a modified Transformer encoder with specialized attention mechanisms for bioacoustic signals, and a set of task-specific output heads for classification and interpretation. Each component has been carefully designed to maintain computational efficiency while achieving state-of-the-art accuracy on feline vocalization tasks.

Moving from the high-level architectural design to implementation specifics requires careful consideration of how raw audio signals are transformed into a format suitable for Transformer processing. The input representation stage serves as this critical bridge, converting time-domain waveforms into structured spectral patches while preserving the nuanced acoustic features that distinguish different types of cat vocalizations. This transformation must maintain temporal relationships while optimizing computational efficiency for edge deployment scenarios.

2.1 Input Representation

The audio preprocessing stage employs a multi-step transformation to extract maximally informative features from raw vocalization signals as follows.

First step: Time-Frequency Analysis

(1) 40ms Hann windows provide optimal resolution for capturing transient vocal events

(2) 50% overlap ensures continuity while maintaining computational efficiency

(3) 128-bin Mel-scale mapping emphasizes perceptually relevant frequency ranges

Second setp: Dynamic Feature Enhancement:

(1) Delta coefficients capture short-term spectral changes

(2) Delta-Delta coefficients model acceleration patterns in vocal pitch

The spectrogram is converted into a sequence of overlapping patches through the following process as described in Table 1.

Table 1. Table 1: Spectrogram-to-Patch Conversion Parameters and Their Acoustic Significance

Parameter	Specification	Acoustic Relevance
Patch Dimensions	16×16 bins	Captures 128ms temporal segments
Frequency Span	~600Hz per patch	Resolves harmonic stacks in meows
Stride	8 bins	Ensures 50% patch overlap
Projection Depth	64 dimensions	Optimized for edge device memory

The patch embedding strategy provides several key advantages for cat vocal analysis as follows.

(1) Temporal Context Preservation: The overlapping patches maintain continuity across rapid vocal transitions

(2) Computational Efficiency: Reduced sequence length enables real-time processing

(3) Feature Resolution: Each patch captures both spectral and temporal characteristics simultaneously

The implementation of our spectrogram-to-patch conversion involves carefully balanced design decisions that optimize three critical factors: acoustic resolution, computational efficiency, and model performance. Through extensive empirical testing, we established that the 16×16 bin patch size represents the minimal viable unit capable of reliably encapsulating complete acoustic events in feline vocalizations - from short chirps (lasting ~50ms) to extended meows (up to 200ms). The selected stride of 8 bins creates a 50% overlap between adjacent patches, providing essential redundancy for continuous feature tracking while maintaining computational tractability. This overlap proves particularly crucial for analyzing transitional vocal phenomena like frequency-modulated trills or rapidly alternating harmonic structures.

The 64-dimensional projection space was determined through systematic ablation studies comparing

dimensionalities ranging from 32 to 512. This specific configuration achieves an optimal compromise, preserving 92.3% of the original spectrogram's discriminative power (measured via mutual information) while reducing memory requirements by 78% compared to standard 256-dimensional embeddings. As demonstrated in our edge deployment experiments (Section 4), this balance enables real-time operation on resource-constrained devices without compromising the model's ability to distinguish subtle vocal nuances - such as the 5-7Hz frequency modulation patterns characteristic of solicitation purrs versus distress calls.

These parameter choices collectively form a robust front-end processing stage that serves multiple functions: it acts as an acoustic feature condenser, a computational load balancer, and a temporal coherence preserver. By transforming raw spectrograms into this optimized patch representation, we create an input space that is simultaneously rich enough for sophisticated attention-based analysis yet efficient enough for edge deployment. The architecture maintains temporal relationships across patches through learned positional embeddings while the patch content itself captures localized spectro-temporal patterns essential for accurate vocalization classification. This dual-scale representation - local details within patches and global context across patches - proves particularly effective for analyzing the hierarchical structure of cat vocalizations, from brief phonetic elements to complete communicative sequences.

2.2 Transformer Encoder

The Transformer encoder serves as the computational backbone of our cat vocalization analysis system, specifically engineered to process the unique acoustic characteristics of feline vocal patterns. Drawing from established Transformer architectures while introducing key innovations, our encoder design achieves an optimal balance between model capacity and computational efficiency required for edge deployment.

The core architecture employs a multi-head self-attention mechanism with four attention heads operating on a 64-dimensional hidden space. This configuration was carefully selected through extensive ablation studies comparing various head counts and dimensionality combinations. The four-head design demonstrates superior performance in capturing both spectral and temporal relationships within vocalizations while maintaining manageable computational requirements. Each attention head specializes in detecting different types of acoustic patterns, from harmonic structures to temporal modulations, allowing the model to develop a comprehensive understanding of the input spectrogram patches.

The feed-forward network component utilizes a 4× expansion ratio, expanding the 64-dimensional hidden representation to 256 dimensions for intermediate processing. This expansion provides sufficient capacity for learning complex feature transformations while the bottleneck architecture controls parameter growth. A moderate dropout rate of 0.1 is applied throughout the network to prevent overfitting to specific acoustic artifacts while preserving sensitivity to meaningful vocalization patterns. This regularization proves particularly important given the relatively small size of available feline vocalization datasets.

Our architecture introduces two significant modifications to the standard Transformer design to better accommodate bioacoustic signal processing requirements. The locality-enhanced attention mechanism augments traditional self-attention with 1D depthwise convolutions applied to value projections. This hybrid approach combines the benefits of global attention with local spectro-temporal processing, creating a receptive field that is simultaneously broad enough to capture extended vocalization sequences and precise enough to resolve fine acoustic details. The convolutional component introduces a local bias that helps maintain continuity in harmonic structures and formant transitions, which are crucial for distinguishing between similar-sounding but semantically different cat vocalizations.

The gated positional encoding system represents our second major architectural innovation, replacing static positional embeddings with a dynamic, learnable alternative. This system employs separate processing paths for temporal and spectral positional information, each with its own gating mechanism that adjusts positional importance based on acoustic context. The frequency-position embeddings adapt to different vocalization types, while the time-gating mechanisms help the model handle the variable rhythm and duration characteristic of natural cat vocalizations. This adaptive approach proves particularly effective when processing vocalizations ranging from brief 200ms chirps to extended 2-second meow sequences.

Implementation considerations for the encoder design reflect careful balancing of multiple competing requirements. The selected four-head attention configuration emerged as optimal after extensive experimentation, providing significantly better performance than two-head alternatives while avoiding the excessive parameter growth of eight-head designs. The 64-dimensional hidden size was chosen to balance memory constraints with feature richness, preserving the majority of discriminative information while remaining viable for edge deployment. The feed-forward network's expansion factor was tuned to provide adequate nonlinear processing capacity while keeping inference latency within the strict requirements of real-time applications.

Several design elements specifically address the unique characteristics of feline vocal communication. The locality enhancement proves particularly valuable for tracking the rapid frequency modulations found in

trills and chirps, while the gated positional system excels at adapting to the irregular rhythmic patterns of cat vocalizations. The compact architecture efficiently focuses processing resources on the 50Hz-8kHz frequency range that contains the most semantically relevant acoustic information for cat communication, avoiding computational waste on less informative spectral regions.

This carefully optimized encoder architecture represents a significant advancement in applying Transformer models to animal vocalization analysis. The combination of architectural innovations and parameter optimizations yields a system that outperforms baseline Transformer implementations by 6.8% in classification accuracy while simultaneously reducing parameter count by 23%. These improvements, coupled with the model's computational efficiency, make it particularly suitable for deployment in resource-constrained smart pet devices and veterinary diagnostic tools, as demonstrated in our experimental results and edge deployment studies.

2.3 Task-Specific Heads

The task-specific heads represent the final processing stage of our architecture, transforming the encoded representations into actionable outputs for cat vocalization understanding. These specialized components bridge the gap between the abstract features learned by the Transformer encoder and the concrete requirements of practical applications in pet care and veterinary diagnostics.

The classification head employs a linear projection layer followed by softmax activation to map the encoded features to four distinct emotional categories: hunger, pain, affection, and playfulness. This simple yet effective design was chosen after comparative studies with more complex alternatives, as it provides robust performance while minimizing computational overhead. The linear layer reduces the 64-dimensional encoder output to 4 dimensions, each corresponding to one emotional state, with the softmax function converting these into interpretable probability scores. The classification head includes temperature scaling during inference to calibrate the confidence estimates, particularly important for safety-critical applications like pain detection.

For the interpretability head, we implement an attention rollout visualization system that traces how attention flows through the network's layers. This component aggregates attention weights across all heads and layers to produce a heatmap showing which spectrogram regions most influenced the final classification decision. The visualization algorithm employs recursive attention weight multiplication to account for the Transformer's deep architecture, with normalization ensuring the heatmap values remain comparable across different vocalization samples. This interpretability feature serves multiple purposes, from helping veterinarians understand model decisions to enabling researchers to identify new acoustic biomarkers in feline vocalizations.

The classification head incorporates several refinements to handle challenges specific to cat vocal analysis. Class imbalance mitigation techniques, including focal loss adaptation, address the uneven distribution of emotion categories in natural cat communication. The head also implements a confidence thresholding system that flags low-certainty predictions for human review, reducing the risk of misinterpretation for ambiguous vocalizations. These safeguards are particularly crucial given the subtle acoustic differences between some emotional states, such as distinguishing between "hunger" and "affection" meows that may share similar pitch contours but differ in harmonic structure.

The interpretability system provides multiple visualization modes tailored to different user needs. A time-frequency attention heatmap shows which spectral regions and temporal segments contributed most to the classification, while a layer-wise attention flow diagram reveals how information propagates through the network. These visualizations are generated in real-time during inference, with optimization ensuring they add minimal computational overhead. The system also includes a novel "acoustic explanation" feature that annotates the attention heatmap with acoustic terminology, helping non-expert users understand why particular spectrogram regions were significant to the model's decision.

Implementation details reflect careful optimization for practical deployment. The classification head uses 8-bit quantization for its weight matrices, reducing memory usage by 75% with negligible accuracy impact. The interpretability components employ efficient matrix operations that reuse intermediate results from the classification process, minimizing redundant computation. Both heads are designed for plug-and-play operation, allowing easy swapping of alternative configurations for different application scenarios without modifying the core encoder architecture.

These task-specific heads complete our end-to-end system for cat vocalization understanding, providing both actionable classifications and transparent decision-making insights. The classification performance, as measured on our validation set, achieves 94.2% accuracy with particularly strong performance in detecting pain vocalizations (96.1% recall). The interpretability features have proven valuable in both research and clinical settings, with veterinary partners reporting that the attention visualizations help correlate acoustic patterns with physiological states. Together, these components fulfill the dual objectives of accurate emotion recognition and explainable AI, crucial requirements for responsible deployment in pet care applications.

III. EXPERIMENTS

Our experimental framework was designed to rigorously evaluate the model's performance across multiple dimensions, including classification accuracy, computational efficiency, and real-world applicability. The comprehensive testing protocol incorporates both controlled benchmark comparisons and practical deployment scenarios to validate the system's effectiveness in authentic feline vocal analysis tasks. These experiments not only measure quantitative performance metrics but also assess qualitative aspects such as the model's ability to generalize across different cat breeds and age groups.

The quality and diversity of the underlying dataset fundamentally determine the validity of any machine learning evaluation. Our experimental design therefore places particular emphasis on dataset composition and annotation reliability, ensuring that performance measurements reflect true model capabilities rather than dataset artifacts. The following subsections detail how we leverage our carefully curated data resources to conduct meaningful, reproducible experiments that address both technical and practical aspects of cat vocalization analysis.

3.1 Data Set

The experimental validation builds upon two complementary data sources that together provide broad coverage of feline vocal communication patterns. The Lund University Cat Vocalizations dataset contributes 1,200 professionally recorded samples representing controlled acoustic environments, with precise metadata including cat demographics, recording conditions, and behavioral context. This curated collection serves as our gold-standard reference for fundamental performance benchmarking, particularly valuable for its consistent recording quality and expert annotations.

To complement these laboratory-grade samples, we incorporated 3,800 user-collected vocalizations captured through smart feeder devices in home environments. This real-world data introduces essential variability in recording conditions, background noise levels, and cat populations, significantly enhancing the model's practical applicability. The smart feeder recordings were collected over 18 months from 47 different households, capturing natural vocalization behaviors during authentic interaction scenarios. Each recording includes synchronized environmental sensors data (ambient noise levels, time of day, feeding history) that permits more nuanced analysis of contextual factors.

The annotation framework employs a four-category labeling system (Hunger, Pain, Play, Affection) developed through collaboration with feline behavior specialists. A three-tier annotation process ensured label reliability: initial automated screening by basic audio features, verification by trained annotators, and final review by veterinary behaviorists for ambiguous cases. The resulting annotations achieve substantial inter-rater agreement (κ=0.81), with particularly strong consensus on pain vocalizations (κ=0.89). To address class imbalance, we applied strategic sample weighting during training while maintaining the natural distribution in test sets to reflect real-world conditions. Dataset preprocessing included careful quality control measures to ensure experimental validity. All recordings underwent:

(1) Standardized amplitude normalization (-3dBFS target level)

(2) Background noise profiling and classification

(3) Duration trimming to remove non-vocal segments

(4) Spectral quality assessment to identify and exclude corrupted samples

The final dataset splits maintain strict separation between development and evaluation sets, with no individual cat appearing in both training and test sets. This prevents inflated performance metrics from recognizing individual animals rather than general vocalization patterns. The test set composition deliberately over-represents challenging edge cases (e.g., multi-cat environments, senior cat vocalizations) to thoroughly stress-test model robustness.

3.2 Benchmark

Our comprehensive benchmarking framework evaluates model performance across three critical dimensions: predictive accuracy, parameter efficiency, and real-time processing capability. The comparative analysis includes both traditional approaches and our proposed architecture to demonstrate measurable advancements in feline vocalization analysis.

The CNN-1D baseline model establishes a strong conventional reference point, achieving 88.5% accuracy with just 50K parameters. This efficient architecture processes audio frames in 8ms on ESP32 hardware, making it suitable for real-time applications. However, its frame-by-frame processing approach struggles with longer-range temporal patterns in cat vocalizations, particularly missing subtle pitch variations that carry emotional meaning.

LSTM-based models show improved accuracy (90.1%) by modeling temporal sequences, but at significant computational cost. The 120K parameter count and 22ms latency reveal the fundamental challenges of recurrent architectures in edge deployment scenarios. While effective at capturing vocalization dynamics, the

sequential processing nature creates bottlenecks that limit real-time performance, especially for longer vocal sequences.

Our TinyFormer architecture achieves the best balance of these factors, reaching 94.2% accuracy with 95K parameters and 15ms latency. The hybrid design combines the efficiency of convolutional feature extraction with the expressive power of self-attention, enabling it to capture both local spectro-temporal patterns and global vocalization context. The 15ms processing time includes complete end-to-end execution from raw audio to classification output, meeting the stringent requirements for responsive pet care devices. Additional benchmark metrics reveal further advantages:

(1) Energy consumption: 3.2mJ per inference (vs 5.8mJ for LSTM)

(2) Memory footprint: 142KB (including weights and runtime buffers)

(3) Wake-word detection accuracy: 98.4% (reducing false triggers)

These results demonstrate that our architecture successfully overcomes the traditional accuracy-efficiency trade-off, enabling sophisticated vocal analysis on resource-constrained hardware. The benchmarks were conducted using identical input features and test sets for all models, ensuring fair comparison under controlled conditions.

3.3 Attention Mechanism Analysis

The self-attention patterns learned by our model provide fascinating insights into how it processes and interprets feline vocalizations. Through detailed examination of attention heatmaps across multiple layers and heads, we observe that the model automatically learns to focus on acoustically significant regions that align remarkably well with known feline vocal communication principles.

For pain-related vocalizations, the attention weights consistently highlight specific frequency bands between 500-800Hz, where harmonic structures are most pronounced. This finding corroborates veterinary acoustic research showing that cats produce distinctive harmonic stacks in this frequency range when experiencing discomfort. The attention patterns show particular sensitivity to the stability and spacing of these harmonics, with irregular harmonic patterns triggering stronger attention responses. This explains the model's exceptional 96.1% recall rate for pain detection, as these acoustic features are highly diagnostic.

When analyzing hunger-related vocalizations, the model demonstrates a different but equally interpretable attention strategy. The strongest attention focuses on rising pitch contours in the initial 200-300ms of the vocalization, particularly tracking the rate and consistency of pitch increase. Secondary attention concentrates on amplitude modulation patterns in the 1-3Hz range, which our analysis reveals correlates with insistent feeding behaviors. These learned attention patterns mirror findings from feline ethology studies that identify rising pitch as a key solicitation cue.

The attention mechanisms also reveal sophisticated contextual processing capabilities. For longer vocalization sequences, we observe dynamic attention shifts where later layers integrate information from earlier time segments, effectively creating a form of acoustic memory. This explains the model's ability to distinguish between similar-sounding vocalizations that differ in their temporal evolution patterns. The attention heads specialize in different aspects of the signal, with some focusing on spectral features while others track temporal dynamics, creating a comprehensive analysis framework.

Cross-validation with expert annotations shows striking alignment between the model's attention patterns and regions identified by feline behavior specialists. Quantitative analysis indicates an 89.7% overlap between high-attention regions and expert-marked diagnostically significant segments. This high correspondence suggests the model learns biologically meaningful representations rather than superficial artifacts, providing confidence in its decision-making process.

The attention analysis also reveals the model's robustness to acoustic variability. Despite significant differences in vocalization characteristics across breeds and individuals, the core attention patterns remain consistent in their focus on diagnostically relevant features. This explains the model's strong generalization performance observed in our cross-breed validation tests. The attention mechanisms automatically adapt to individual vocalization styles while maintaining focus on the underlying emotionally relevant acoustic cues.

These findings have important practical implications. The interpretable attention patterns allow veterinarians and pet owners to understand and verify the model's decisions, building trust in the system. The attention visualizations also serve as a valuable educational tool, helping humans better understand feline communication cues. Furthermore, the discovered attention patterns may guide future biological studies of cat vocal communication by highlighting potentially significant acoustic features that warrant deeper scientific investigation.

IV. EDGE DEPLOYMENT

The successful deployment of our cat vocalization recognition system on edge devices represents a crucial milestone in enabling real-world applications for pet care and veterinary monitoring. Moving from theoretical models to practical implementations requires addressing numerous challenges unique to resource-constrained environments, including limited computational power, memory constraints, and energy efficiency requirements. Our edge deployment strategy focuses on maintaining the model's analytical capabilities while ensuring reliable performance across diverse hardware platforms, from smart collars to home monitoring systems.

Bridging the gap between the full-precision model and efficient edge deployment requires a systematic optimization pipeline that balances computational efficiency with model accuracy. The following techniques have been carefully developed and validated to preserve the model's core functionality while meeting the stringent requirements of edge devices. Each optimization method addresses specific deployment challenges while maintaining the interpretability and reliability essential for animal health applications.

4.1 Optimization Techniques

Our optimization framework employs a multi-stage approach to adapt the model for edge deployment without compromising its diagnostic capabilities. The quantization-aware training process converts the model from FP32 to INT8 precision through simulated quantization during training, allowing the network to adapt to reduced numerical precision. This technique achieves a 3.2× speedup in inference time while maintaining 98.7% of the original model's accuracy. The quantization process pays particular attention to preserving the dynamic range in attention score calculations, which are crucial for the model's interpretability features.

Block-wise pruning represents our second optimization pillar, strategically removing 40% of attention heads based on their contribution to overall performance. Our evaluation metric considers both the head's individual importance and its redundancy within the full network. The pruning process preserves heads specializing in critical frequency bands (particularly the 500-800Hz pain detection range) while eliminating redundant temporal analysis heads. This approach yields a 45% reduction in memory usage with merely a 0.8% accuracy drop, and notably, has minimal impact on the attention visualization quality.

For deployment on NVIDIA edge devices, we implemented a TensorRT engine optimized specifically for feline vocal processing. The engine incorporates layer fusion for CNN-Transformer hybrid operations and specialized kernels for spectrogram patch processing. On the Jetson Nano platform, this achieves consistent 5ms/sample inference latency while consuming under 2W of power. The engine supports dynamic batching to handle multiple concurrent audio streams, a critical feature for smart home deployments with several pets. Additional optimization strategies include:

(1) Memory-aware architecture redesign that reduces peak memory usage by 60%
(2) Selective activation caching that decreases memory bandwidth requirements
(3) Energy-proportional computing that adjusts model complexity based on power budget
(4) Adaptive batch processing optimized for variable-length vocalizations

These optimizations collectively enable deployment across a wide range of edge devices while maintaining the model's core functionality. The optimized version retains 93.4% of the original model's accuracy while achieving:

(1) 3.8× faster inference than the baseline implementation
(2) 72% reduction in memory footprint
(3) 5× improvement in energy efficiency
(4) Full compatibility with standard edge AI accelerators

The optimization process also includes comprehensive testing under real-world conditions, verifying performance across different microphone qualities, ambient noise levels, and vocalization intensities. This ensures reliable operation in actual home environments where consistent power and ideal recording conditions cannot be guaranteed.

4.2 Memory-Efficient Variant

To address the stringent memory constraints of ultra-low-power devices like the ESP32-S3 with its limited 320KB PSRAM, we developed specialized model variants through innovative architectural refinements. These solutions enable sophisticated cat vocal analysis on resource-constrained hardware while maintaining clinically relevant accuracy levels through careful balancing of model complexity and performance.

The Distilled TinyFormer represents our most compact architecture, achieving a remarkable reduction to just 48K parameters while maintaining 87.6% classification accuracy. This was accomplished through a novel layer-wise distillation process that carefully preserves the most crucial aspects of our full-sized model's knowledge. The distillation maintains the original model's interpretability by emphasizing attention-map matching during training, ensuring the compact version still focuses on biologically meaningful acoustic

features. Emotion-specific distillation weights help the smaller network preserve its diagnostic capability for critical conditions like pain detection, while progressive layer shrinking optimizes the architecture for memory efficiency without abrupt performance degradation.

Our Hybrid CNN-Transformer approach takes a complementary route to memory efficiency by strategically blending convolutional and attention mechanisms. The design centers around an initial CNN layer that performs intelligent sequence length reduction while preserving spectro-temporal relationships. Using depthwise separable convolutions with large 8×8 kernels and learned pooling, this layer achieves a 4:1 reduction ratio before the signal reaches the transformer blocks. This architectural choice dramatically decreases memory requirements for subsequent attention computations while maintaining the model's ability to capture both local and global vocalization patterns.

Memory optimization permeates every aspect of these variants, from sparse attention patterns in higher layers to dynamic memory allocation strategies that adapt to variable-length inputs. The implementations feature flash-based parameter storage and streaming spectrogram processing to maximize the limited available memory. Attention cache optimization and selective layer loading further reduce peak memory usage below 280KB during inference, leaving necessary headroom for other system operations.

These memory-conscious designs maintain the original model's clinically valuable interpretability features through carefully preserved attention mechanisms that still highlight diagnostic frequency bands. The compressed versions generate compatible visualization outputs, enabling continued use in veterinary and pet owner applications. Field testing across 120+ household deployments has demonstrated the variants' reliability in real-world conditions, with consistent 87-88% accuracy across different cat breeds and environments.

The memory-efficient implementations open new possibilities for deployment in ultra-low-power devices like smart collars and distributed home sensors, where they operate on minimal power budgets while providing advanced vocal analysis capabilities. This technological advancement makes sophisticated AI-based animal health monitoring accessible on affordable, widely available hardware platforms, potentially transforming how we understand and respond to feline communication needs.

V. CONCLUSIONS

This work demonstrates that Transformer architectures represent a significant advancement in cat vocalization recognition, providing context-aware analysis that surpasses traditional RNN and CNN approaches. The self-attention mechanism's ability to model long-range dependencies in spectro-temporal features proves particularly effective for capturing the nuanced acoustic patterns in feline communication. Our experiments show consistent improvements across multiple metrics, with the Transformer-based model achieving superior accuracy while maintaining computational efficiency suitable for edge deployment.

The success of our approach stems from several key innovations. The locality-enhanced attention mechanism bridges the gap between global context modeling and local spectro-temporal pattern recognition, crucial for analyzing brief yet complex cat vocalizations. The gated positional encoding system adapts to variable-length vocalizations while preserving temporal relationships. Together, these advancements enable more biologically faithful interpretation of feline vocal signals compared to frame-based conventional methods.

Looking forward, three important research directions emerge from this work. First, multimodal Transformer architectures combining audio with visual inputs could significantly enhance interpretation accuracy by incorporating complementary behavioral cues like ear position and tail movements. Preliminary experiments suggest such multimodal approaches might resolve current ambiguities between similar-sounding vocalizations with different meanings. Second, few-shot adaptation techniques need development to personalize models for individual cats, whose vocal signatures can vary substantially. This capability would be particularly valuable for monitoring pets with chronic conditions requiring precise vocal change detection.

Finally, the growing capability of AI-based pet interpretation systems necessitates parallel development of ethical guidelines. Important considerations include establishing reliability standards for health-related interpretations, protecting pet privacy in cloud-based systems, and preventing over-reliance on automated interpretation at the expense of human-animal interaction. The attention visualization features in our system represent an initial step toward explainable AI for pet owners and veterinarians.

The broader implications of this work extend beyond technical achievements. By providing more accurate tools for understanding feline communication, we enable earlier detection of health issues, improved human-animal bonding, and potentially new insights into feline cognition and emotion. The successful deployment on edge devices makes these benefits accessible to everyday pet owners, not just research settings. As the field progresses, maintaining scientific rigor while ensuring practical utility will remain paramount in developing AI systems that truly enhance our understanding and care of companion animals.

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