A Whisker of Truth: A Multimodal Interdisciplinary Machine Learning Approach to Vocal, Visual, and Tactile Signals in the Domestic Cat

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Abstract

We propose a multimodal deep learning framework for automated analysis of cat–human communication, integrating acoustic, visual, and tactile signals through transformer-based fusion. Using the largest expert-annotated dataset of its kind and interdisciplinary collaboration, we combine semi-supervised learning with ethological and phonetic expertise to detect subtle behavioural and phonetic cues, enable early welfare assessment, and establish species-generalisable methods.

1 Background

Humans and cats have had a mutual tolerance for millenia [1] and with an estimated 600 million cats worldwide [2] they are one of the most common companion animals. Despite this, the communication habits of our feline companions remain poorly understood. Studies in recent years have made progress in deciphering cats' ability to recognise individual humans [3] and their own names [4], as well as their use of multimodal signals in interactions with humans [5, 6]. Yet, automated behaviour analysis using machine learning techniques remains under-explored or lack expert involvement [7]. Others raise bias concerns due to absence of appropriate subject grouping mechanism across train and test sets [8].

Cats communicate through a rich repertoire of visual, behavioural, and vocal signals. They use visual cues to convey intentions during interactions with humans [9], and behavioural signals can influence adoption outcomes in shelters [10]. They also demonstrate social awareness, adapting their communication to human attentiveness [11]. Their vocal repertoire is extensive and variable, shaped by learning to better express needs and emotions to humans [12, 13]. Additionally we know that vocal prosody of the domestic cat varies with physical context [14]. Humans remain poor interpreters of these signals - even experienced cat owners achieve only modest accuracy when classifying vocalisations [15], and subtle visual expressions such as jaw drop or upper lip raise are often overlooked [16]. Misinterpretation of these signals risks compromising feline welfare, as unmet needs can manifest in undesired behaviours, abandonment, or relinquishment.

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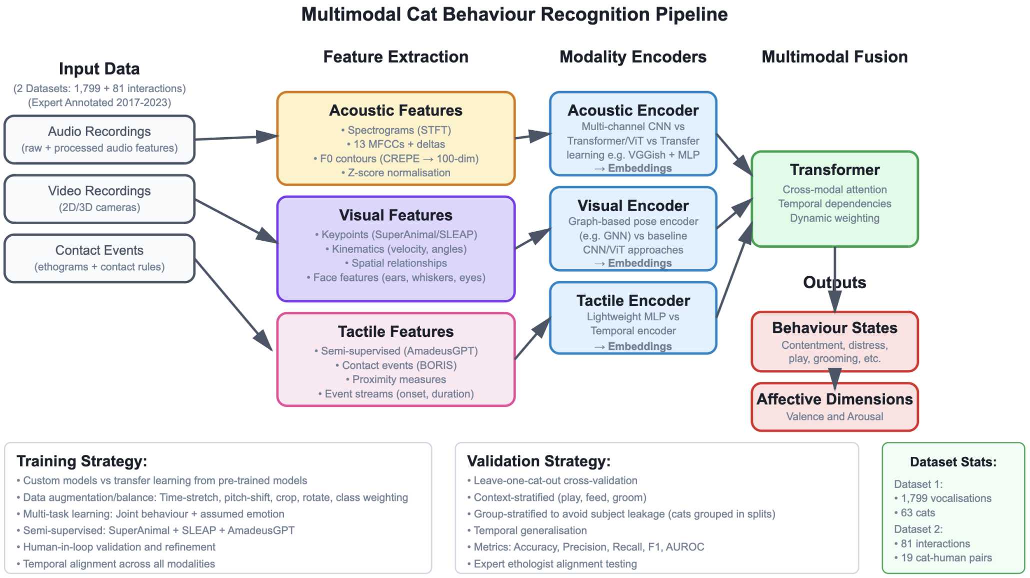
Deep learning has been effective in recognising specific cat vocalisations [17] and age related vocalisation changes [18], with emerging applications such as automated pain detection through facial analysis [19] and behavioural classification using accelerometry through wearable sensors [20]. While these studies demonstrate the potential of individual modalities, there is a notable gap in research combining acoustic, visual, and behavioural data for holistic understanding of feline communication and welfare assessment. Current approaches treat each modality in isolation, missing the rich interplay between vocalisations, facial expressions, and body language that characterises natural feline communication. Additionally, tactile data is still lacking in the literature - marking a promising frontier.

This gap highlights the urgent need for systematic, automated approaches that integrate expertise from phonetics, ethology, and machine learning that our proposal aims to address. AI-driven multimodal systems hold particular promise in bridging the gap between feline communication and human understanding, enabling new tools to support both research and everyday welfare monitoring. Previous AI systems (e.g., MeowTalk) have yielded disappointing results, in part due to a lack of integration with linguistic and behavioural expertise. By contrast, our team brings together internationally recognised expertise in feline phonetics (Susanne Schötz) and ethology (Elin Hirsch), and specialism in machine learning for bioacoustics analysis (Astrid van Toor). Importantly, our methods are strictly non-invasive, relying on naturalistic recordings and expert annotation to avoid stress to the animals. While our immediate focus is on cats, the methodology generalises to other species, addressing a broader challenge in AI for animal communication.

2 Proposed approach


Multimodal Cat Behaviour Recognition Pipeline
Input Data
(2 Datasets: 1,799 + 81 interactions)
(Expert Annotated 2017-2023)
Audio Recordings
(raw + processed audio features)
Video Recordings
(2D/3D cameras)
Contact Events
(ethograms + contact rules)
Feature Extraction
Acoustic Features
• Spectrograms (STFT)
• 13 MFCCs + deltas
• F0 contours (CREPE → 100-dim)
• Z-score normalisation
Visual Features
• Keypoints (SuperAnimal/SLEAP)
• Kinematics (velocity, angles)
• Spatial relationships
• Face features (ears, whiskers, eyes)
Tactile Features
• Semi-supervised (AmadeusGPT)
• Contact events (BORIS)
• Proximity measures
• Event streams (onset, duration)
Modality Encoders
Acoustic Encoder
Multi-channel CNN vs Transformer/ViT vs Transfer learning e.g. VGGish + MLP
→ Embeddings
Visual Encoder
Graph-based pose encoder (e.g. GNN) vs baseline CNN/ViT approaches
→ Embeddings
Tactile Encoder
Lightweight MLP vs Temporal encoder
→ Embeddings
Multimodal Fusion
Transformer
Cross-modal attention
Temporal dependencies
Dynamic weighting
Outputs
Behaviour States
Contentment, distress, play, grooming, etc.
Affective Dimensions
Valence and Arousal

Training Strategy:

- Custom models vs transfer learning from pre-trained models
- Data augmentation/balance: Time-stretch, pitch-shift, crop, rotate, class weighting
- Multi-task learning: Joint behaviour + assumed emotion
- Semi-supervised: SuperAnimal + SLEAP + AmadeusGPT
- Human-in-loop validation and refinement
- Temporal alignment across all modalities

Validation Strategy:

- Leave-one-cat-out cross-validation
- Context-stratified (play, feed, groom)
- Group-stratified to avoid subject leakage (cats grouped in splits)
- Temporal generalisation
- Metrics: Accuracy, Precision, Recall, F1, AUROC
- Expert ethologist alignment testing

Dataset Stats:

Dataset 1:
- 1,799 vocalisations
- 63 cats

Dataset 2:
- 81 interactions
- 19 cat-human pairs

Figure 1: Complete machine learning workflow

2.1 Data

We leverage the largest expert-annotated multimodal datasets of cat-human interactions to date, comprising synchronised audio, video, and behavioural annotations from naturalistic home environments between 2017-2023. All interactions were recorded with two cameras (one head-mounted, one filming the whole scene). Meowsic [21] comprises of 1799 cat vocalisations and interactions from 63 individual cats and 36 humans, of which the acoustics have been expertly annotated by Schötz - our specialist in cat phonetics - and her prior research team [21]. Extensive acoustic features have been pre-extracted and behaviours annotated through a double-blind review process. These cats were observed vocalising at each other as well as with humans. Call types were classified based on phonetic

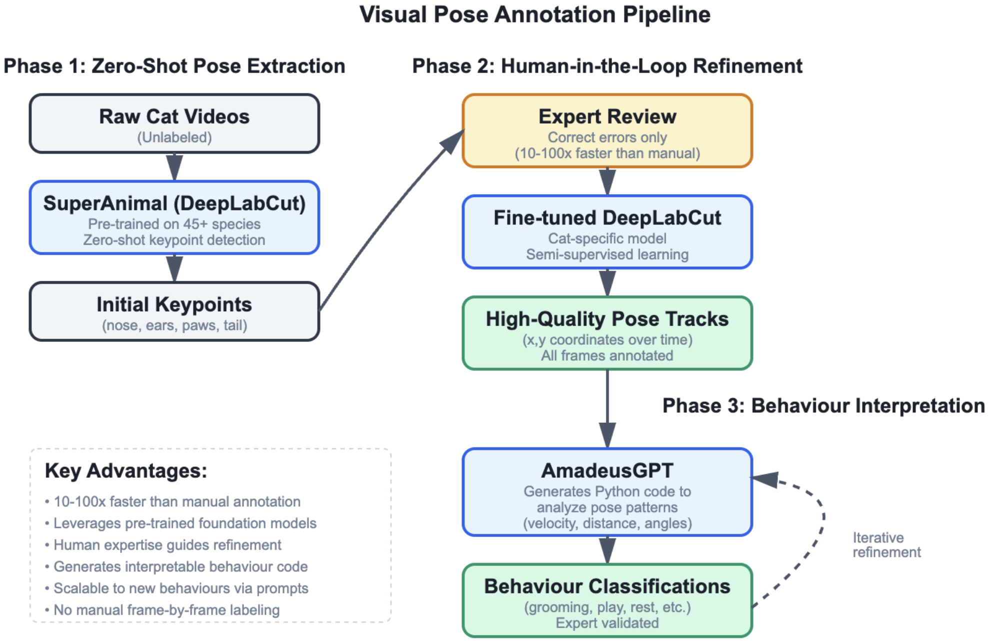

Visual Pose Annotation Pipeline
Phase 1: Zero-Shot Pose Extraction
Phase 2: Human-in-the-Loop Refinement
Raw Cat Videos
(Unlabeled)
SuperAnimal (DeepLabCut)
Pre-trained on 45+ species
Zero-shot keypoint detection
Initial Keypoints
(nose, ears, paws, tail)
Expert Review
Correct errors only
(10-100x faster than manual)
Fine-tuned DeepLabCut
Cat-specific model
Semi-supervised learning
High-Quality Pose Tracks
(x,y coordinates over time)
All frames annotated
Phase 3: Behaviour Interpretation
Key Advantages:
• 10-100x faster than manual annotation
• Leverages pre-trained foundation models
• Human expertise guides refinement
• Generates interpretable behaviour code
• Scalable to new behaviours via prompts
• No manual frame-by-frame labeling
AmadeusGPT
Generates Python code to
analyze pose patterns
(velocity, distance, angles)
Behaviour Classifications
(grooming, play, rest, etc.)
Expert validated
Iterative
refinement

Figure 2: Pose annotation workflow

features according to [22]. Further visual and tactile signals will be annotated as per the pipeline outlined in Figure 2 and elaborated on in the following paragraph. The cat-human-communication (CHC) dataset [5] captures 81 readily annotated interactions across 19 cat-human pairs with frame-level annotations for acoustic events (vocalisations, pitch contours), visual behaviours (ear positions, facial expressions, posture), and tactile interactions (contact initiation, stroking patterns). Only healthy cats were included in the trials. Metadata about the cats' and owners' experience, familiarity, and individual characteristics were collected via online questionnaires based on [21]. Owners also provided information about their cats' personality.

We are aware of the importance of scalability and have outlined plans for expanding data collection; given that factors such as breed, age, sex, housing conditions, location, and seasonal changes are known to influence behaviour [20], we will continue expanding our data collection efforts to build upon our existing foundation and achieve more comprehensive representation across these key variables leveraging the previous framework and recording equipment [21, 10] (see also Appendix B1). Our validation strategy (Section 2.6) furthers ensures generalisation to unseen individuals, and the modular architecture supports adaptation to larger datasets and new contexts.

As for breeds, in the Meowsic dataset more than half of the cats were housecats or mixed breeds, whereas the others constituted a variety of different pure breeds including Maine Coon, Bengal and Siamese [21]. The CHC dataset also includes mainly housecats and mixed breeds (including Persian-Norwegian Forest Cat and Persian-Maine Coon).

Due to the absence of comparable expert-annotated multimodal cat-human interaction datasets, traditional state-of-the-art comparisons are not feasible. Our work establishes the first comprehensive benchmark in this domain, pioneering a foundation for future comparative studies.

2.2 Annotation

To scale annotation beyond manual labelling we employ a semi-supervised pipeline combining tools such as SuperAnimal [23] and SLEAP [24] for automated keypoint extraction with human-in-the-loop refinement. This approach reduces annotation time by 10-100x [23] while maintaining expert-level accuracy. Importantly, annotation is an ongoing, iterative process central to this project. We are actively developing comprehensive ethograms based on the latest research [25–27] and our emerging findings, rather than relying solely on existing classifications. This iterative approach allows us to identify context-dependent and relationship-specific behavioural patterns (e.g., how tail elevation differs between cats with varying human familiarity) that static ethograms may overlook. Semi-supervised tactile identification is obtained by feeding time-series pose data to AmadeusGPT [28] to generate hypotheses like: "*Cat ear angle changed immediately after contact onset → tactile influence on behaviour*", which are then validated and refined by our expert team. While AmadeusGPT is emerging, it has demonstrated robustness across multiple benchmarks including the MABe 2022 challenge, cross-species validation (mice, horses), and stress-testing with out-of-distribution prompts achieving 88% consistency. The tool has been validated with a random sample of real user queries showing practical reliability.

Remaining multimodal communicative signals will be coded using the event-logging software BORIS [29] and ethograms developed in earlier studies [25, 26, 30]. All modalities will be temporally aligned to common frame and sample rates.

2.3 Multimodal Feature Extraction

Our approach extracts complementary features from each modality, designed to capture the full spectrum of feline communicative signals:

- **Acoustic**: A triple feature stack representation of (1) spectrograms via STFT, (2) 13 MFCCs plus deltas encoding perceptual characteristics, and (3) fundamental frequency (f0) contours extracted via CREPE [31] resampled to 100-dimensional vectors for multi-channel neural network input. All features undergo z-score normalisation computed on the training set.
- **Visual**: Keypoint coordinates from SuperAnimal [23] / SLEAP [24] are augmented with derived kinematic features (velocities, accelerations, inter-joint angles). We encode spatial relationships between key body parts (ear-to-ear distance, tail curvature, head-to-body angle) that may correlate with affective states. Face-specific features include ear angle relative to head, whisker position, and pupil dilation where visible.
- **Tactile**: Annotated human–cat contact events through semi-supervised analysis using AmadeusGPT [28] and BORIS [29] (touch, stroking, play) for pose-based features (proximity of cat and human limbs). These signals are encoded as event streams (onset, duration, type of contact), which are passed through a lightweight MLP or temporal encoder. This allows the model to capture the role of tactile interaction in shaping cat communicative behaviour, despite the absence of direct tactile sensors.

2.4 Architecture and training strategy

Each signal will employ a modality-specific neural network to act as feature extractor. These embeddings are then processed by a transformer network that learns cross-modal attention patterns and temporal dependencies from time-series data. We hypothesise that this architecture allows the model to dynamically weigh the importance of different modalities over time. For example prioritising acoustic features during vocalisations, visual cues during silent displays, or analysing their combinations when signals co-occur, such as a meow that shifts meaning depending on accompanying posture or tactile context. For the individual modalities we will explore a number of feature extraction methods such as; custom multi-channelled convolutional neural networks (section 2.3), embeddings from prominent pre-trained neural network feature extractors (e.g. VGGish [32], AmadeusGPT [28]) followed by downstream multilayer perceptron processing, transformer extractors, graph neural networks for skeletal structure modelling of pose sequences, and transfer learning by fine-tuning robust pre-existing models. Consequently this work will present a comparative review of SOTA machine learning techniques in digital bioacoustics and computer vision for animal pose. We will include a variety of data augmentation techniques such as time-stretching and pitch-shifting for audio, and random cropping and rotation for video, with class weighting to address potential behavioural imbalance.

Our end-to-end pipeline processes raw video input through sequential stages: (1) pose estimation using SLEAP/SuperAnimal for keypoint detection, (2) multimodal feature extraction including kinematic, acoustic, and tactile signals, (3) behavioural pattern learning and deviation detection, and (4) automated report generation with optional expert validation for continuous improvement. The pipeline is illustrated in Fig. 1.

2.5 Error Mitigation

We acknowledge that multi-stage pipelines can accumulate errors. To address this we will: (1) validate each component independently (pose estimation accuracy, behavioural annotation consistency, multimodal fusion performance), (2) implement confidence scoring at each stage to flag uncertain outputs, and (3) use expert-in-the-loop validation to catch and correct propagated errors.

Modern pose estimation frameworks have demonstrated high accuracy that minimise error propagation in downstream tasks. SLEAP achieves a mAP score of 0.927 and DeepLabCut (DLC) of 0.928, with SLEAP being faster than DLC at 2,194 versus 458 FPS [24, 33]. SuperAnimal, built on DeepLabCut, further enhances data efficiency by requiring 10-100× less labelled data than standard transfer-learning approaches while maintaining high accuracy [23]. These foundation models can perform zero-shot inference across 45+ species including cats, demonstrating robust generalisation to diverse imaging conditions and animal morphologies. For challenging scenarios with occlusions or ambiguous poses, SLEAP's confidence scoring system allows uncertainty quantification at the keypoint level, which we will leverage to flag low-confidence detections for manual review.

Rather than relying on fixed threshold-based rules, our approach emphasises learned behavioural patterns from annotated data and deviation detection from individual baselines. We acknowledge that concrete behavioural thresholds (e.g., specific ear angles indicating discrete emotional states) remain an area of active research. Instead, our system learns to identify general indicators of potential concern—such as tail positions suggesting stress, changes in movement patterns, or altered response patterns to familiar humans—which flag cases for further investigation rather than making definitive classifications. AmadeusGPT serves as a complementary tool for discovering complex spatio-temporal patterns and enabling natural language behavioural queries. Critically, we leverage the rich contextual metadata in our datasets (cat-human familiarity, interaction history, environmental setting) to develop context-aware models that account for relationship-specific behavioural nuances.

2.6 Evaluation

To prevent subject leakage that may have been compromised in previous studies [8], and to ensure scientific rigour, we will employ robust and industry-standard validation strategies namely leave-one-cat out cross-validation to assess generalisation to new individuals, cross-validated hold-out validation, and context- and group-stratified validation ensuring all contexts and individual cats are represented equally and separately across train and test sets. We measure the model's ability across context through accuracy, precision, recall, f1-score, and AUROC measures. In addition to standard machine learning metrics, we will evaluate the system's potential for real-world usability by testing how well the models align with expert ethologists' annotations and whether predictions generalise across home environments.

3 Expected outcomes and impact

Our project provides the first comprehensive, multimodal architecture for domestic cat vocal, visual, and tactile signals, providing open-source benchmarks and datasets to advance the field of computational animal behaviour. By establishing ground-truth ethograms and healthy behavioural baselines, we aim to automate welfare assessments such as subtle facial expression changes or shifts in vocal prosody or touch that humans struggle to perceive. This reduces observer bias and enables earlier detection of stress, pain, or illness. While our focus is on domestic cats, the proposed framework generalises readily to other species. The modular multimodal pipeline (acoustic, visual, tactile) can be adapted to diverse animal communication contexts, supporting comparative ethology and cross-species welfare studies.

The design supports a fully automated, personalised pipeline through modular integration of pose estimation, feature extraction, and behavioural analysis. A critical component is personalised baseline modelling: the general model, pre-trained on our diverse multi-cat dataset, learns broad communication patterns, then fine-tunes on individual user recordings of their cat during healthy periods. In production, the system operates through a two-stage process: (1) users establish an individualised baseline through multiple healthy-period recordings, and (2) subsequent recordings are analysed for deviations that flag potential welfare concerns. This deviation-based approach addresses individual variation in communication style, breed differences, and unique cat-human relationship dynamics—for example, tail elevation patterns may differ between cats with strong versus weak human attachment, or play behaviour may manifest differently across breeds and age groups. Rather than diagnosing specific conditions, the system identifies general indicators (altered movement patterns, changes in responsiveness, shifts in typical communication) warranting closer examination. Optional expert review services can provide interpretation of flagged cases, with anonymised production data feeding back into model refinement through active learning to continuously improve detection capabilities.

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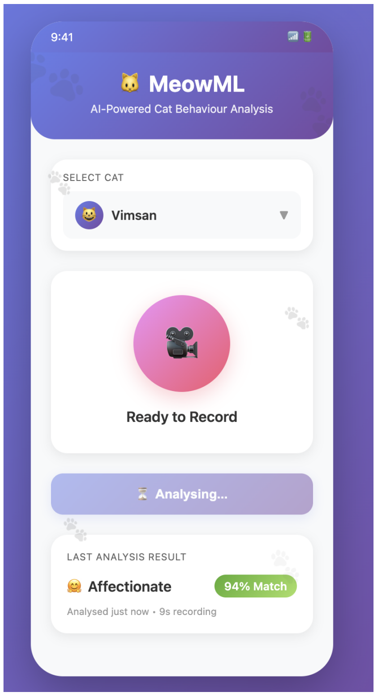
A Supplementary Figures



SELECT CAT

Vimsan

LAST ANALYSIS RESULT

Affectionate 94% Match

Analysed just now • 9s recording

Figure 3: Mobile application mock-up interface for cat behaviour analysis. In production the app records synchronised audio-visual data to assess behavioural cues.

B Methodological and Ethical Details

B.1 Addressing Limitations

Beyond the data collection variables mentioned in the main text, key limitations include cross-cultural differences in human-cat interactions patterns that may affect model transferability. Throughout our work we will continue data collection in different locales. For an eventual production-level application we would strive to include Explainable AI (XAI) technologies to explain the parameters for certain predictions.

Our behavioural annotation framework is deliberately iterative and data-driven. We are building comprehensive ethograms that integrate established research with novel patterns emerging from our multimodal analysis. This includes capturing context-dependent behaviours (e.g., how approach behaviour differs based on prior interaction history), relationship-specific signals (e.g., vocal prosody variations between familiar versus unfamiliar humans), and subtle welfare indicators that may not appear in existing ethograms (e.g., micro-expressions or postural changes preceding overt stress signals). By combining expert ethological knowledge with data-driven pattern discovery, we aim to create more nuanced and accurate behavioural classifications than those based solely on historical categorical systems.

The new datasets will be collected with the same setup as the one used in the CHC dataset [10]. Additionally, we will expand the dataset through systematic data collection across multiple contexts and environments, including homes, clinics, and shelters. This includes high-quality multimodal recordings (audio, 2D/3D video), annotated using expert-developed ethograms and acoustic–phonetic analysis tools (e.g., Praat, BORIS). These efforts are designed to ensure diversity in breed, age, familiarity, and interaction types, thereby supporting both model training and generalisation.

Our mobile application will incorporate an optional active learning component where users can contribute anonymised data to improve model performance. With explicit user consent, videos undergo automatic privacy protection (face masking, audio filtering) before expert review, creating a continuous feedback loop for model refinement while maintaining strict privacy standards.

B.2 Computational Requirements

Training the multimodal deep learning architecture requires GPU clusters with expectedly 300-400 GPU hours for full model development across all modalities. Inference would be optimised for mobile consumer-level hardware, and computationally heavy processing would be hosted on external servers.

B.3 Ethics and Consent Procedures

All human participants provide informed consent via GDPR-compliant forms detailing data collection, storage, and sharing procedures. Consent includes permission for research use and open dataset release under CC-BY-NC license. Participants complete recording sessions following standardised protocols with full procedure disclosure. Cat welfare is monitored throughout recordings with immediate cessation protocols if stress indicators are observed.

The project adheres to all ethical and professional considerations outlined by the relevant national Ethical Review Authorities, institutional policies, informed consent following the GDPR [34] and confirms to the ARRIVE guidelines for animal research.

B.4 Data Management and Asset Documentation

New datasets include comprehensive metadata covering recording conditions, participant demographics, and annotation procedures. Data sharing agreements specify research use permissions and anonymisation protocols. Code repositories will include detailed documentation, installation instructions, and reproduction scripts. Existing asset licenses are verified and documented: SuperAnimal (Apache 2.0), SLEAP (BSD-3), BORIS (GPL-3). All derived works maintain appropriate attribution and license compatibility.

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   Question: Do the main claims made in the abstract and introduction accurately reflect the paper's contributions and scope?

   Answer: [Yes]

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2. **Limitations**

   Question: Does the paper discuss the limitations of the work performed by the authors?

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   Question: For each theoretical result, does the paper provide the full set of assumptions and a complete (and correct) proof?

   Answer: [NA]

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   Question: Does the paper specify all the training and test details (e.g., data splits, hyperparameters, how they were chosen, type of optimizer, etc.) necessary to understand the results?

   Answer: [NA]

   Justification: As this is a proposal for future work without completed experiments, specific hyperparameters, training details, and exact methodological specifications are not yet available. The proposal outlines the intended approach.

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   Question: Does the paper report error bars suitably and correctly defined or other appropriate information about the statistical significance of the experiments?

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- It is OK to report 1-sigma error bars, but one should state it. The authors should preferably report a 2-sigma error bar than state that they have a 96% CI, if the hypothesis of Normality of errors is not verified.
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   Answer: [NA]

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    Question: Does the paper discuss both potential positive societal impacts and negative societal impacts of the work performed?

    Answer: [Yes]

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