Beyond Closed-Set Assumptions: Advancing Open-Set Problem with Adaptive Learning

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Introduction. Despite significant AI advances in computer vision, existing approaches remain confined to *closed-set* assumptions, where all classes, data distributions, and input features stay fixed over time [6]. However, real-world applications rarely exhibit such static conditions: models may confront data from unknown classes, new sensor modalities, or evolving distributions [1]. These *open environment* problem require novel theoretical and algorithmic perspectives to achieve Open-World Learning. Our research focuses on two particularly critical problems: (1) *Emerging New Classes,* which necessitate continuous discovery and integration of novel categories without forgetting previously learned ones, and *Changing Data Distributions,* which mandate continuous adaptation to phenomena like *covariate shift*, *concept drift*, or altered sensor conditions. Such factors exceed the scope of conventional "known vs. unknown" methods, each of which typically covers only a *subset* of the broader problem space. This gap motivates our main Research Questions (RQ) which are: RQ1:*How can we formulate a comprehensive taxonomy for open-environment learning, and assess if today's solutions effectively cover all dimensions of this definition?*, RQ2: *How to detect and classify out-of-distribution and unknown classes?*, RQ3: *How to automatically update open-set detection and recognition models with new features and emerging classes?*, and RQ4: *How to make open-set detection and recognition models explainable?*

Related Work. Open-environment learning draws upon four overlapping research areas: *Anomaly Detection (AD)* typically formulates the problem in a binary sense, "normal vs. anomalous", and often merges *all* known classes into a single normal category [3]. While AD captures outliers, it does not explicitly handle new class emergence nor domain shifts and their increment/decrement of features. *Novelty Detection* considers new classes under stable input distributions but lacks mechanisms for changes in *both* label and feature space [5]. *Open-Set Recognition (OSR)* extends classification to reject unknowns, yet commonly treats everything outside training labels as one broad "unknown" [2]. *Out-of-Distribution (OOD) Detection* focuses on distribution mismatch [4], but rarely disentangles sensor-driven changes from newly emerging classes.

Proposed Approach / Research Plan. We propose a holistic open-environment framework underpinned by:

- **Formal Taxonomy:** Categorizing real-world samples into In-distribution Known, In-distribution Unknown, Out-of-distribution Known, and Out-of-distribution Unknown.
- **OOD Detection using Spectral Decomposition:** For RQ2, we are developing a spectral decomposition approach that constrains the eigenvalue spectrum for robust feature extraction and generalization. By enforcing a power-law decay, we align learned representations with data distributions, improving OOD detection and reducing overfitting.
- **Adaptive Learning Mechanisms:** We will design incremental modules to update learned representations without retraining from scratch (RQ3), mitigating catastrophic forgetting.
- **Explainable Decisions:** Incorporating interpretability will address RQ4 by clarifying why the model flags certain samples as unknown.

Anticipated Contributions

1. **Unified Taxonomy:** A clear conceptual framework categorizing unknown inputs and data shifts beyond simple binary distinctions.
2. **Algorithmic Innovation:** Novel approaches, enabling robust discrimination of new classes vs. domain changes, and incrementally learn novel features and classes without catastrophic forgetting.
3. **Explainability for Open-environment:** Mechanisms to visualize why certain samples are flagged.

Timeline: Year 1 focused on finalizing the taxonomy, literature survey (RQ1), and designing a spectral decomposition-based methodology (RQ2). In **Year 2** we will extend and validate this approach on real-world image data (RQ2) while implementing incremental learning for new classes and features (RQ3). **Year 3** involves designing explainable open-set interfaces (RQ4), final experiments, writing, and defense preparation.

References

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