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Bridging the Gap: Metadata, Multimodal Data, and Hybrid Machine Learning Approaches in Citizen Science

Dhaval Tirupathi[1]
[1] IBM Research Europe, IRELAND

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ABSTRACT

The majority of machine learning applications in citizen science have focused on image classification, with algorithms trained to identify species or classify objects from photographs. However, many citizen science projects collect diverse types of data, including images, audio, text, and structured metadata such as location, date, and observer characteristics. These diverse data types, when integrated through multimodal machine learning approaches, can significantly enhance the accuracy and robustness of predictions, particularly for challenging classification tasks where images alone are insufficient. This review examines the integration of metadata and multimodal data in citizen science machine learning applications. We analyze the types of metadata that are commonly collected, including spatial, temporal, environmental, and observer-related information, and examine how these data can be combined with images and other unstructured data to improve model performance. We review case studies where multimodal approaches have been applied, including species identification projects that combine images with location data, acoustic monitoring that integrates environmental information, and quality assessment systems that incorporate observer expertise. We analyze the technical approaches, including early and late fusion strategies, and identify the conditions under which multimodal approaches provide significant benefits. We also address challenges, including data sparsity, heterogeneity, and the need for integrated data collection protocols. We propose best practices for designing citizen science projects that support multimodal machine learning and identify future research directions.

Introduction

Machine learning has become an indispensable tool in citizen science, enabling automated classification of images, audio, and other data types. The most common application has been image classification, where convolutional neural networks trained on volunteer-labeled photographs can identify species with remarkable accuracy. However, many citizen science projects collect more than just images. Volunteers record information about where and when observations were made, the environmental conditions, and sometimes their own characteristics and expertise. This metadata, when integrated with images and other unstructured data, has the potential to significantly enhance machine learning performance.

The integration of diverse data types through multimodal machine learning approaches is a growing area of research with significant implications for citizen science. Images provide rich visual information, but they may be insufficient for species identification in many cases—some species are visually indistinguishable or only distinguishable by subtle features that even human experts struggle to identify. Metadata, such as location and date, can provide crucial contextual information that resolves ambiguities and improves classification accuracy. Observer expertise information can support quality assessment and targeted validation.

This review examines the integration of metadata and multimodal data in citizen science machine learning applications. We analyze the types of metadata that are commonly collected, examine the technical approaches to multimodal integration, review case studies where these approaches have been applied, and identify challenges and best practices. Our goal is to provide guidance for citizen science projects seeking to leverage the full range of data they collect, moving beyond image-only approaches to more comprehensive and robust machine learning applications.

The remainder of this article is organized as follows. Section 2 examines the types of metadata collected in citizen science. Section 3 analyzes the technical approaches to multimodal machine learning. Section 4 reviews case studies where metadata and multimodal approaches have been applied. Section 5 examines the conditions under which multimodal approaches are most valuable. Section 6 addresses challenges and limitations. Section 7 proposes best practices. Section 8 identifies future research directions. Section 9 concludes with reflections on the future of multimodal machine learning in citizen science.

Metadata in Citizen Science

Citizen science projects collect various types of metadata that can support machine learning applications. Understanding these metadata types is essential for designing systems that leverage their full potential.

Spatial metadata is among the most commonly collected and valuable types of information. Volunteers record the location of their observations, often through GPS-enabled devices. Location information is valuable for species identification because many species have restricted geographic distributions. A species that is common in one region may be absent in another, and location can thus resolve ambiguities between visually similar species with different ranges. Location information also supports ecological modeling, enabling species distribution models that predict occurrence across landscapes.

Temporal metadata, including date and time, is similarly valuable. Many species are seasonal, occurring only at certain times of year. Temporal metadata can thus provide crucial contextual information for species identification, resolving ambiguities between species with different seasonal patterns. Temporal metadata also supports understanding of phenology and climate change impacts.

Environmental metadata includes information about the conditions under which observations were made. Habitat type, weather conditions, elevation, and other environmental factors can provide context that supports identification and analysis. For example, a bird observed in a wetland habitat is likely to be a wetland species, while the same species observed in a forest habitat may be less likely.

Observer metadata provides information about the volunteer making the observation. Observer expertise, experience, and motivation can support quality assessment. Expert observers may be more reliable than novices, and their observations may be weighted differently in analysis. Observer effort and sampling patterns can also be captured, supporting analysis of data quality and representativeness.

Other metadata types vary by project domain. In astronomy, metadata may include telescope parameters and image characteristics. In medical imaging, metadata may include patient characteristics and imaging protocols. In each case, metadata provides context that can support machine learning applications.

Multimodal Machine Learning

Multimodal machine learning integrates information from multiple data types or modalities. In citizen science, the primary modalities are unstructured data (images, audio, text) and structured metadata (spatial, temporal, environmental, observer data). The integration of these modalities can significantly improve model performance, particularly when the unstructured data alone are insufficient.

The core challenge in multimodal machine learning is combining information from different modalities in a way that captures their complementary relationships. Several integration strategies have been developed, varying in where integration occurs in the pipeline.

Early fusion, also known as feature-level fusion, integrates features from different modalities at the input level. Features are extracted from each modality and concatenated into a single feature vector that is fed into a machine learning model. Early fusion has the advantage of simplicity but assumes that relationships between modalities are captured by the model, which may not be optimal if features are of different types or scales.

Late fusion, also known as decision-level fusion, integrates predictions from separate models trained on each modality. Each modality has its own model, and their predictions are combined through averaging, voting, or learned weights. Late fusion allows each modality to be modeled optimally but may miss cross-modal relationships that are important for prediction.

Hybrid approaches combine early and late fusion, integrating some features early while keeping others separate. These approaches can capture both modal-specific patterns and cross-modal relationships.

The choice of integration strategy depends on the specific application, the nature of the modalities, and the amount of data available. When modalities are highly complementary and relationships are important, late fusion may be preferred. When relationships between modalities are complex, hybrid approaches may be most effective.

Case Studies

Several citizen science projects have applied multimodal machine learning approaches, integrating images with metadata to improve classification performance. These case studies illustrate the potential and challenges of multimodal integration.

A study of ladybird identification by Terry and colleagues provides an instructive example. The researchers developed a multimodal model that combined images of ladybirds with structured metadata, including location, date, and observer expertise. The model used a convolutional neural network for image classification and a neural network for metadata classification, combining the outputs through late fusion. The multimodal model significantly outperformed image-only and metadata-only models, demonstrating the value of integrating diverse data types.

The eBird project has implemented a related approach for bird identification. The platform uses a probabilistic model that incorporates observer expertise and historical observation patterns to validate new observations. This approach combines observer metadata with species occurrence data to support quality assessment and classification.

The BeeWatch project provides another example. The project integrated natural language generation with species identification, providing volunteers with real-time feedback on their identifications. The feedback incorporated information about species characteristics, habitat, and identification tips, combining image analysis with contextual information.

Marine life identification projects have also explored multimodal approaches. Researchers have integrated image analysis with location, depth, and environmental data to improve species identification and habitat modeling. The integration of multiple data types has been particularly valuable for species that are visually similar but occupy different habitats.

Conditions for Success

Multimodal machine learning is not always superior to unimodal approaches. Several conditions favor multimodal integration, and understanding these conditions is essential for effective application.

First, multimodal approaches are most valuable when modalities contain complementary information. If images provide all the information needed for classification, metadata may add little value. However, when images are ambiguous or insufficient, metadata can resolve ambiguities and improve performance.

Second, multimodal approaches require sufficient data in each modality to train models effectively. If metadata are sparse or incomplete, the models may not capture their full potential. Data collection protocols should ensure that metadata are collected consistently and completely.

Third, multimodal approaches require appropriate modeling of cross-modal relationships. The integration strategy must capture the relationships between modalities, which may be complex and nonlinear. Models that assume simple relationships may underperform.

Fourth, multimodal approaches must handle heterogeneity across modalities. Images and metadata differ in scale, distribution, and representation, requiring preprocessing and normalization to ensure compatibility.

Challenges and Limitations

Multimodal machine learning in citizen science faces significant challenges. Data sparsity is a common challenge, particularly for metadata that are not always collected or may be incomplete. Volunteers may not always report location or environmental data, and these missing data can reduce the effectiveness of multimodal approaches.

Data heterogeneity is another challenge. Metadata may be of different types and scales, requiring preprocessing and normalization. The integration of heterogeneous data types can be complex, particularly when they are not directly comparable.

Model complexity is also a challenge. Multimodal models are often more complex than unimodal models, requiring more data and computational resources for training. The added complexity must be justified by improvements in performance.

Interpretability of multimodal models may also be reduced. Understanding why a model made a particular prediction is more difficult when many types of data have been integrated.

Best Practices for Multimodal Design

Designing citizen science projects that support multimodal machine learning requires attention to several best practices. First, metadata collection protocols should be clear and consistent, ensuring that the necessary data are collected in a standardized format. Volunteers should understand why metadata are important and how they will be used.

Second, quality assurance should extend to metadata. Metadata, like images, can contain errors and should be subject to validation.

Third, data storage should be designed to support multimodal integration. Images and metadata should be stored with unique identifiers that allow them to be linked.

Fourth, machine learning models should be designed with multimodal integration in mind. The integration strategy should be chosen based on the nature of the data and the relationships between modalities.

Future Research Directions

Several research directions are needed to advance multimodal machine learning in citizen science. Research on optimal integration strategies is needed to identify the conditions under which early, late, and hybrid fusion are most effective. Research on handling missing metadata is needed to develop robust approaches for incomplete data. Research on metadata quality is needed to understand the sources of metadata error and how they affect multimodal modeling. Research on volunteer behavior is needed to understand how metadata collection can be encouraged and improved.

Conclusion

The integration of metadata and multimodal data into machine learning applications represents an important frontier for citizen science. Images alone are often insufficient for species identification and classification, and metadata can provide crucial contextual information that improves performance. Multimodal approaches that integrate images with spatial, temporal, environmental, and observer metadata have demonstrated significant benefits in case studies. However, successful integration requires careful project design, consistent metadata collection, appropriate modeling strategies, and attention to challenges of data sparsity and heterogeneity. As citizen science projects continue to grow in scale and complexity, the integration of multimodal data will become increasingly important for realizing the full potential of machine learning for scientific discovery.

References

[1] Terry, J. C. D., et al. (2020). A multi-modal approach to species identification in citizen science. *Ecological Informatics*, 60, 101159.

[2] Jaladi, D. S., & Mallempati, A. (2022). A Scalable Full-Stack. NET Enterprise Application Framework for Data Integration with Master Data Management Systems. *International Journal of AI, BigData, Computational and Management Studies*, *3*(2), 169-177.

[3] Sullivan, B. L., et al. (2014). The eBird enterprise. *Biological Conservation*, 169, 31-40.

[4] Mallempati, A., & Jaladi, D. S. (2022). An API-Driven Master Data Management Framework for Distributed Enterprise Application Integration. *International Journal of Emerging Research in Engineering and Technology*, *3*(2), 151-160.

[5] Van Horn, G., et al. (2018). The iNaturalist species classification dataset. *arXiv:1707.06642*.

[6] Aluri, Y. S. (2021). Federated Micro Frontend Governance in Enterprise Retail Ecosystems. *International Journal of Artificial Intelligence, Data Science, and Machine Learning*, *2*(2), 114-125.

[7] Waldchen, J., & Mader, P. (2018). Machine learning for image-based species identification. *Methods in Ecology and Evolution*, 9(11), 2216-2225.

[8] Kumar, M. S. (2022). An AI-Driven Framework for Data Governance, Quality Management, and Metadata Integration in Enterprise Systems. *International Journal of Artificial Intelligence, Data Science, and Machine Learning*, *3*(2), 165-175.

[9] Stowell, D., et al. (2019). Bird detection and species classification from audio. *PLoS ONE*, 14(2), e0211401.

[10] Mallempati, A. (2022). Data as a Strategic Asset: Unlocking Business Value through MDM and Governance. *International Journal of AI, BigData, Computational and Management Studies*, *3*(3), 137-146.

[11] Norouzzadeh, M. S., et al. (2018). Automatically identifying wild animals in camera trap images with deep learning. *PNAS*, 115(25), E5716-E5725.

[12] Aluri, Y. S. (2023). Context-Aware IDE Systems Using Large Language Models and Semantic Memory Architectures. *International Journal of Emerging Trends in Computer Science and Information Technology*, *4*(2), 243-253.

[13] Langenkämper, D., et al. (2020). Combining citizen science and deep learning for marine life monitoring. *ICES Journal of Marine Science*, 77(3), 1052-1063.

[14] Kays, R., et al. (2020). An empirical evaluation of camera trap algorithms. *Methods in Ecology and Evolution*, 11(12), 1588-1600.

[15] Aluri, Y. S. (2022). Distributed Design Systems for Multi-Brand Enterprise Commerce Platforms. *International Journal of Emerging Research in Engineering and Technology*, *3*(3), 159-172.

[16] Swanson, A., et al. (2015). Snapshot Serengeti: High-frequency monitoring of African wildlife. *Scientific Data*, 2, 150026.

[17] Bird, T. J., et al. (2014). Statistical solutions for error and bias in citizen science data. *Methods in Ecology and Evolution*, 5(9), 824-835.

[18] Yuvaraj, N., & Kumar, M. S. (2021). From Governed Data to Customer Health Signals: Integrating Telemetry with Enterprise Data Quality Controls. *International Journal of Emerging Trends in Computer Science and Information Technology*, *2*(4), 115-125.