Solent University

Department of Science and Engineering

Feasibility Study on Automated Fish Species Classification Using Hybrid Deep Learning Models (Pilot Study)

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Introduction

The aim of this pilot study is to explore the feasibility of using image data to identify different species of fish. Accurate identification of fish species is essential for various applications such as biodiversity conservation, fisheries management, and ecological research. Traditional methods are often labour-intensive and prone to error. This study will employ advanced image processing and machine learning techniques to automate and enhance the accuracy of fish species classification. The project will be divided into two parts: this pilot study, which serves as a feasibility report, and the main project, which includes a comprehensive analysis and practical implementation.

Background and Justification

Problem Statement

The identification of fish species is crucial for various applications, including biodiversity conservation, fisheries management, and ecological research. Traditional methods of species identification are often time-consuming, require expert knowledge, and can be prone to human error. Automated image-based classification systems offer a promising solution to these challenges by providing a scalable, efficient, and accurate alternative.

Research Question: How effective are machine learning techniques in classifying fish species based on image data?

Justification

This research will leverage existing datasets and advanced machine learning algorithms to create a robust classification system. By analysing and processing a diverse set of fish images, the study aims to develop a model that can accurately identify fish species. This has significant implications for environmental monitoring and resource management, potentially leading to more informed decision-making processes in these areas.

Dataset Details

Fish Species dataset currently consisting of 3,960 images collected from 468 species. Data consists of real-world images of fish captured in 3 conditions defined as "controlled", "out-of-the-water" and "in-situ".

The "controlled", images consists of fish specimens, with their fins spread, taken against a constant background with controlled illumination.

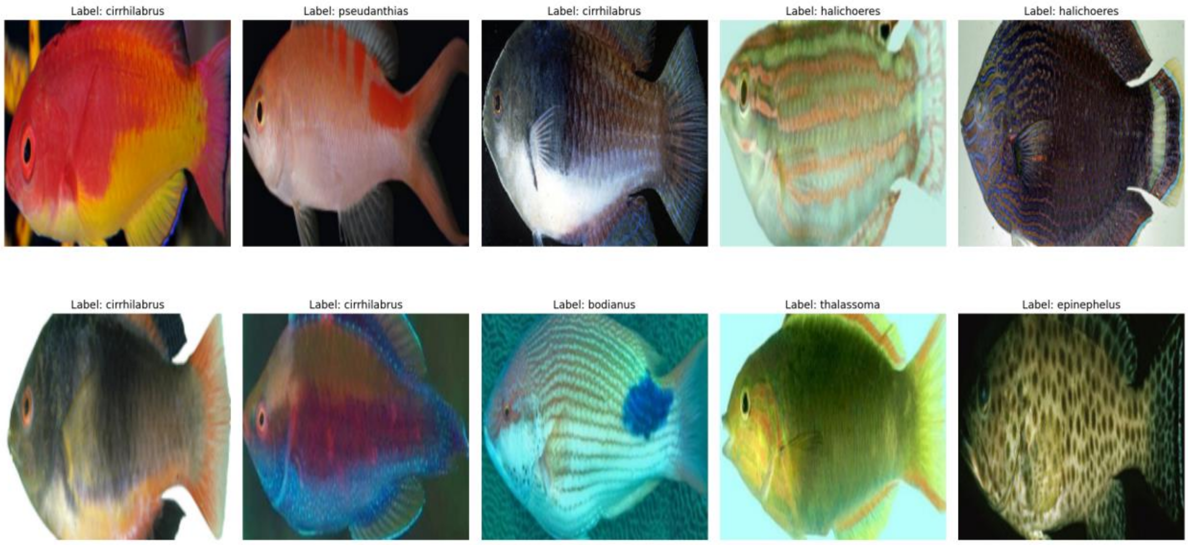

Figure 1, a grid of sample images

The "in-situ" images are underwater images of fish in their natural habitat and so there is no control over background or illumination. The "out-of-the-water" images consist of fish specimens, taken out of the water with a varying background and limited control over the illumination conditions. (1)

Literature Review

Recent advancements in fish species identification have leveraged sophisticated computational techniques to improve classification accuracy and efficiency.

Climent-Perez et al. (2024) presented a comprehensive workflow for simultaneous fish instance segmentation, species classification, and size regression from uncalibrated images of fish trays at wholesale markets. Their research addresses the critical need for accurate biomass estimation and fisheries management in response to global overexploitation issues. The study achieved an overall mean average precision (mAP) of 70.42% for fish instance segmentation and species classification, demonstrating robust performance in identifying and categorizing fish species from complex market environments. Additionally, their size estimation method yielded a mean average error (MAE) of only 1.27 cm, showcasing high accuracy in quantifying fish sizes automatically. This work highlights the potential of computer vision and machine learning in transforming fisheries data collection and management, providing valuable insights for sustainable resource exploitation and conservation efforts. (2)

Kaur and Vijay (2024) introduced an Invariant Feature-based Species Classification (IFSC) model using a pattern-net-based Convolutional Neural Network (CNN) for species identification in underwater environments. Their research focused on octopus and crab species, achieving an impressive accuracy of 95.04%. The IFSC model employed the Speed Up Robust Feature (SURF) descriptor for invariant feature extraction and utilized a genetic algorithm (GA) for feature selection, addressing challenges such as variable lighting, species concealment, and irregular backgrounds in underwater images. This study represents a significant advancement in the field, demonstrating the efficacy of deep learning techniques for accurate species classification in challenging environmental conditions. (3)

Dharshana et al. (2023) introduced a novel approach using a You Only Look Once (YOLO) architecture-based method for the detection and classification of fish species in underwater environments. Their research addresses the challenges of manual labour and potential inaccuracies in fish categorization by automating the process through deep neural networks. The YOLO architecture enables real-time object detection and classification, utilizing contextual information from the environment to enhance species inference. The study focused on a diverse dataset including gilt head bream, trout, red sea bream, sea bass, and other species, demonstrating improved discrimination capabilities compared to traditional methods. This approach represents a significant advancement in underwater fish classification, overcoming challenges such as image distortion, background noise, and occlusions prevalent in underwater imagery. (4)

Malik et al. (2023) introduced a novel Fish Detection Network (FD_Net) based on an enhanced YOLOv7 algorithm for the automated detection and classification of nine different fish species using camera-captured images. Their research addresses the challenges of underwater video sampling, including ambient luminance changes, fish camouflage, dynamic environments, and watercolour effects. The FD_Net utilizes improvements such as MobileNetv3 and depth wise separable convolutions in its feature extraction network to enhance feature extraction capability and widen the receptive field. The study achieved a mean average precision (mAP) that is 14.29% higher than the initial YOLOv7 version, demonstrating superior performance compared to other state-of-the-art models like YOLOv3, YOLOv4, and Faster-RCNN in complex underwater environments. This approach represents a significant advancement in automated fish species identification, offering robust solutions for marine conservation and biodiversity monitoring efforts. (5)

In 2022, Smith et al. introduced an innovative approach leveraging transfer learning for fish species identification. By utilizing pre-trained neural networks on large, diverse datasets, they were able to achieve superior accuracy while significantly reducing the required training time and computational resources. This method involved fine-tuning pre-trained models to adapt to specific fish species datasets, effectively transferring learned features from generalized domains to specialized tasks. The study demonstrated the efficacy of transfer learning in enhancing model performance for biological image classification, particularly in scenarios with limited annotated data. Smith et al.'s work highlighted the potential of transfer learning to expedite the development of accurate and efficient classification systems in various biological and ecological research applications. (6)

Methodology

Data Collection

Dataset Overview: The dataset comprises 3,960 images from 468 fish species. Images are captured in three different conditions: "controlled", "out-of-the-water", and "in-situ".

- Controlled: Fish specimens with fins spread, taken against a constant background with controlled illumination.
- Out-of-the-Water: Fish specimens taken out of the water with a varying background and limited control over illumination.
- In-situ: Underwater images of fish in their natural habitat with no control over background or illumination.

Data Preprocessing

Image Annotation: Ensure each image is correctly labelled with the corresponding fish species.

Data Augmentation: Apply transformations such as rotation, scaling, flipping, and cropping to increase the diversity of the training data and prevent overfitting, especially important given the varying conditions of the images.

Image Resizing: Standardize the size of all images to 200x200 pixels to maintain consistency across the dataset.

Condition Labelling: Tag each image with its condition (controlled, out-of-the-water, in-situ) to later analyse the model's performance under different conditions.

Model Selection

Baseline Models: Start with traditional machine learning models such as k-Nearest Neighbours (k-NN), Support Vector Machines (SVM), and Random Forest to establish baseline performance.

Deep Learning Models: Implement Convolutional Neural Networks (CNNs) such as VGG16, ResNet50, and MobileNet, which are known for their efficacy in image classification tasks.

Condition-Specific Models: Consider training separate models for each condition (controlled, out-of-the-water, in-situ) to compare performance and identify condition-specific challenges.

Model Training

Training-Validation Split: Divide the dataset into training (70%), validation (20%), and test (10%) sets, ensuring each split has a representative sample of all conditions and species.

Hyperparameter Tuning: Use techniques such as grid search and random search to find the optimal hyperparameters for each model.

Training Process: Train each model using the training set while monitoring performance on the validation set to avoid overfitting. Employ early stopping to prevent overfitting by terminating training when the validation performance stops improving.

Model Evaluation

Performance Metrics: Evaluate models using metrics such as accuracy, precision, recall, F1-score, and confusion matrix.

Cross-Validation: Perform k-fold cross-validation (k=5) to ensure the robustness of the models and to mitigate the risk of overfitting.

Model Validation

Test Set: Use the independent test set to assess the final performance of the models. Ensure that the test set includes images from all three conditions to evaluate generalization.

Comparative Analysis

Baseline vs. Advanced Models: Compare the performance of traditional machine learning models with deep learning models to determine the most effective approach for fish species classification.

Condition-Specific Analysis: Analyse model performance on images from each condition (controlled, out-of-the-water, in-situ) to identify any discrepancies or biases in classification.

Implementation

Software and Tools: Use Python as the primary programming language along with libraries such as TensorFlow, Keras, Scikit-Learn, and OpenCV.

Hardware Requirements: Utilize GPUs to accelerate the training process, particularly for deep learning models.

Aims and Objectives

Aim

To develop a machine learning model that can accurately classify fish species based on image data.

Objectives:

- Conduct a comprehensive literature review on fish species classification methods, incorporating at least 5 recent studies.
- Define evaluation metrics (accuracy, F1-score, computational efficiency) to identify the most effective approach for species classification.
- Quantify dataset characteristics: Analyse the dataset to determine the number of images per species and ensure balanced representation.
- Develop and validate machine learning models: Implement CNNs and hybrid models to achieve a minimum accuracy of 80% on test data.
- Address ethical considerations: Ensure compliance with ethical guidelines for animal data usage and privacy concerns related to image collection.

Proposed Artefact and Societal Impact

Artefact

The primary artefact of this research will be a trained machine learning model capable of classifying fish species from images. This model will be accompanied by a user-friendly interface that allows users to upload images and receive predictions.

Societal Impact

The developed classification system has the potential to streamline fish species identification processes in various sectors. It can aid in biodiversity studies by providing accurate species counts, support fisheries management by ensuring sustainable practices, and assist in ecological research by offering reliable data on species distribution. Additionally, the system can be used in citizen science projects, engaging the public in environmental monitoring efforts.

Project Implementation

Project Plan

- Phase 1 (Weeks 1-2): Conduct literature review and define research question.
- Phase 2 (Weeks 3-4): Perform EDA and preprocess the dataset.
- Phase 3 (Weeks 5-6): Develop and train initial machine learning models.
- Phase 4 (Weeks 7-8): Evaluate model performance and perform error analysis.

- Phase 5 (Weeks 9-10): Finalize the model and develop the user interface.
- Phase 6 (Week 11): Prepare the study report and submit.

Gantt Chart

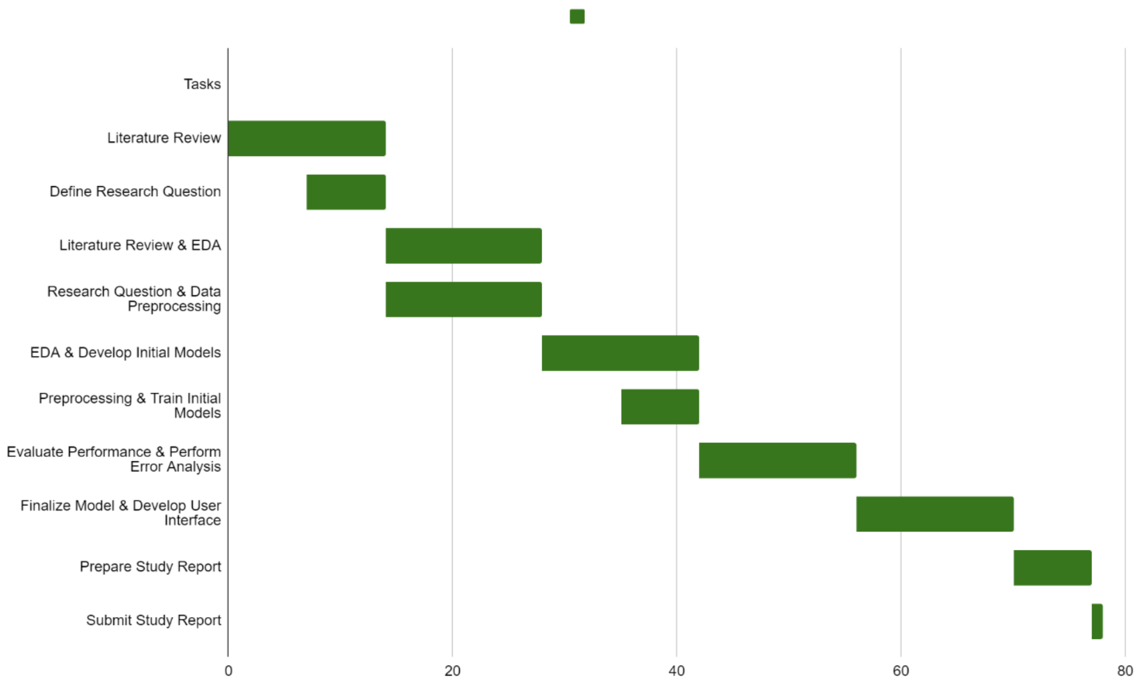

Figure 2, Gantt Chart of project plan

Conclusion

This pilot study aims to demonstrate the feasibility of using hybrid deep learning models for fish species classification based on image data. By addressing the outlined objectives and leveraging advanced image processing and machine learning methods, the study seeks to contribute to the development of an efficient and accurate classification system. The successful implementation of this project has the potential to significantly impact environmental monitoring, fisheries management, and ecological research, providing a scalable solution for species identification.

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