Coral Health Detection Model Using SVM

Class-Wise Confidence Analysis

The class-wise confidence scores provide a detailed insight into the model's predictive behavior for each test image. Instead of only showing the predicted class and its confidence, this approach reveals the probabilities assigned to both classes: **Healthy Coral (Class 0)** and **Bleached Coral (Class 1)**.

Key Benefits:

1. **Improved Transparency:**
   - By displaying the confidence for both classes, users can evaluate the certainty of predictions, especially in cases where the probabilities are close, indicating ambiguity.
2. **Error Analysis:**
   - Helps in identifying misclassified samples where the confidence for the incorrect class is high. This information can guide improvements in preprocessing or model design.
3. **Actionable Insights:**
   - Enables better understanding of model performance for domain experts, particularly in ecological or conservation contexts, where the distinction between healthy and bleached corals is critical.

Predicted label

```
Image 1: Predicted Class = 1, Class 0 = 0.34, Class 1 = 0.66
Image 2: Predicted Class = 1, Class 0 = 0.03, Class 1 = 0.97
Image 3: Predicted Class = 0, Class 0 = 0.93, Class 1 = 0.07
Image 4: Predicted Class = 1, Class 0 = 0.02, Class 1 = 0.98
Image 5: Predicted Class = 0, Class 0 = 0.56, Class 1 = 0.44
Image 6: Predicted Class = 0, Class 0 = 0.85, Class 1 = 0.15
Image 7: Predicted Class = 0, Class 0 = 0.99, Class 1 = 0.01
Image 8: Predicted Class = 0, Class 0 = 0.52, Class 1 = 0.48
Image 9: Predicted Class = 1, Class 0 = 0.12, Class 1 = 0.88
Image 10: Predicted Class = 1, Class 0 = 0.03, Class 1 = 0.97
Image 11: Predicted Class = 0, Class 0 = 0.74, Class 1 = 0.26
Image 12: Predicted Class = 1, Class 0 = 0.11, Class 1 = 0.89
Image 13: Predicted Class = 1, Class 0 = 0.35, Class 1 = 0.65
Image 14: Predicted Class = 1, Class 0 = 0.49, Class 1 = 0.51
Image 15: Predicted Class = 0, Class 0 = 0.52, Class 1 = 0.48
Image 16: Predicted Class = 0, Class 0 = 0.83, Class 1 = 0.17
Image 17: Predicted Class = 0, Class 0 = 0.79, Class 1 = 0.21
Image 18: Predicted Class = 0, Class 0 = 0.83, Class 1 = 0.17
Image 19: Predicted Class = 1, Class 0 = 0.23, Class 1 = 0.77
Image 20: Predicted Class = 0, Class 0 = 0.66, Class 1 = 0.34
Image 21: Predicted Class = 1, Class 0 = 0.37, Class 1 = 0.63
Image 22: Predicted Class = 0, Class 0 = 0.88, Class 1 = 0.12
Image 23: Predicted Class = 1, Class 0 = 0.46, Class 1 = 0.54
Image 24: Predicted Class = 1, Class 0 = 0.31, Class 1 = 0.69
Image 25: Predicted Class = 0, Class 0 = 0.51, Class 1 = 0.49
Image 26: Predicted Class = 0, Class 0 = 0.78, Class 1 = 0.22
Image 27: Predicted Class = 0, Class 0 = 0.91, Class 1 = 0.09
Image 28: Predicted Class = 0, Class 0 = 0.60, Class 1 = 0.40
Image 29: Predicted Class = 0, Class 0 = 0.53, Class 1 = 0.47
Image 30: Predicted Class = 1, Class 0 = 0.42, Class 1 = 0.58
```

Predicted probabilities for both classes are displayed for every test image.

Confusion Matrix Analysis

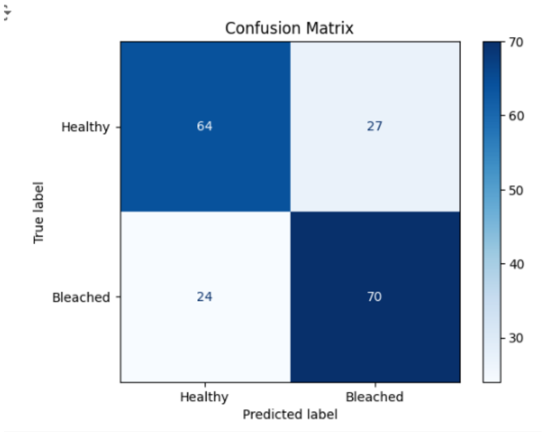
The confusion matrix provides a visual representation of the model's classification performance by summarizing predictions across actual and predicted classes. It highlights the number of correct and incorrect predictions for each class, allowing for a detailed error analysis.

Key Benefits:

1. **Classification Errors:**
   - Clearly identifies where the model misclassifies samples (false positives and false negatives).
2. **Strengths in Classification:**

- Demonstrates areas where the model performs well, such as correctly identifying healthy or bleached corals.

3. **Balanced Evaluation:**
    - Offers insights into imbalanced predictions, helping to assess whether the model favors one class over another.

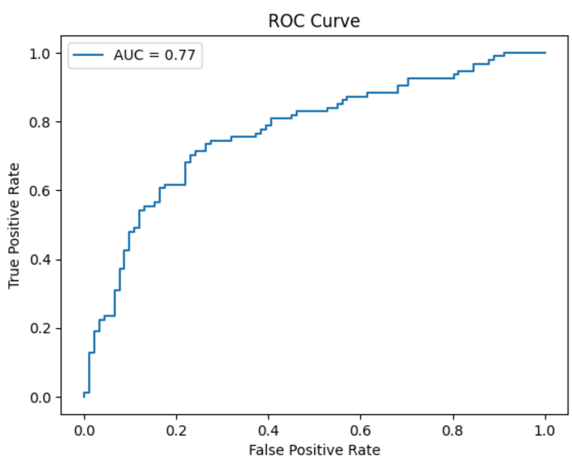


ROC Curve Analysis

The ROC (Receiver Operating Characteristic) curve is a powerful tool for evaluating the performance of a classification model. It plots the True Positive Rate (TPR) against the False Positive Rate (FPR) at various classification thresholds. This curve provides a comprehensive view of the model's ability to distinguish between classes across different sensitivity levels.

Key Benefits:

1. **Threshold Selection:**
    - The ROC curve helps identify the optimal classification threshold by balancing the TPR and FPR, ensuring the best trade-off between sensitivity and specificity.
2. **Model Comparison:**
    - By comparing the ROC curves of different models, we can assess which model performs better at discriminating between classes.
3. **AUC (Area Under Curve):**
    - The AUC value quantifies the overall performance. A higher AUC indicates better model performance, with an AUC of 1.0 representing perfect classification.



Ideas and Further Analysis for SVM in Coral Bleaching Prediction

1. Enhancing Input Data Quality

- **Incorporate Diverse Datasets:**
  Use multi-source data, including satellite imagery, in situ measurements, and historical event records.
- **Temporal Analysis:**
  Include temporal features such as seasonality, cumulative heat stress (e.g., Degree Heating Weeks), and event duration.
- **Anthropogenic Indicators:**
  Add data on overfishing, coastal pollution, and land-use changes to capture human-induced stressors.

2. Advanced Feature Engineering

- **Interaction Terms:**
  Create features that capture interactions between environmental variables, such as SST and pH or wind speed and solar irradiance.
- **Geospatial Features:**
  Use geographic attributes like reef depth, distance to shore, and regional biodiversity indices.
- **Trend Analysis:**
  Develop features based on temporal trends, such as SST rise rates or cumulative DHM over recent years.

3. Model Optimization

- **Kernel Selection:**
  Experiment with different kernel functions (e.g., RBF, polynomial) to capture non-linear relationships.
- **Parameter Tuning:**
  Use techniques like grid search or Bayesian optimization to fine-tune SVM hyperparameters (C, gamma, etc.).
- **Class Imbalance Handling:**
  Employ oversampling (SMOTE) or weighted SVM to address imbalances in healthy vs. bleached coral data.

4. Integration with Other Models

- **Hybrid Models:**
  Combine SVM with clustering algorithms (e.g., k-means or hierarchical clustering) for zoning and targeted prediction.
- **Ensemble Learning:**
  Use SVM as part of an ensemble model with Decision Trees, Random Forests, or Gradient Boosted Machines for improved accuracy.

5. Scalability and Real-Time Application

- **Incremental Learning:**
  Implement SVM variants like online SVM for real-time learning as new data becomes available.
- **Distributed Computing:**
  Leverage cloud-based platforms for handling large datasets and deploying real-time SVM predictions.

6. Equity and Accessibility

- **Localized Models:**
  Develop regional SVM models tailored to specific reefs and communities, incorporating local environmental and socio-economic conditions.
- **Community Data Sharing:**
  Collaborate with local stakeholders to collect and share data, fostering inclusivity in model development.

7. Evaluation Metrics and Bias Mitigation

- **Comprehensive Metrics:**
  Evaluate beyond accuracy, using metrics like sensitivity, specificity, and Matthews correlation coefficient (MCC).
- **Bias Auditing:**
  Regularly assess and mitigate biases in predictions, especially in data-scarce regions.

8. Applications Beyond Coral Bleaching

- **Ecosystem Monitoring:**
  Extend SVM models to predict related phenomena, such as algal blooms, fish migration patterns, or biodiversity changes.
- **Policy Support:**
  Use SVM outputs to inform adaptive management strategies, zoning plans, and resource allocation.

Future Analysis Goals

- **Global vs. Local Models:**
  Assess the trade-offs between global SVM models and region-specific versions.
- **Multi-Scale Analysis:**
  Evaluate performance at different scales (reef, regional, global) and temporal resolutions.
- **Uncertainty Quantification:**
  Incorporate techniques like bootstrapping or Monte Carlo simulations to quantify prediction uncertainty and improve decision-making reliability.