Your Smart Guide to Surf Conditions

SwellSight

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Motivating Use Case

Use Case Background

Surfers rely on low-quality beach-camera images to decide when to surf conditions. These images provide visual information but lack objective measurements

Problem

- **Subjectivity:** Current wave assessment is based on guesswork and varies across surfers and locations.
- **Lack of Data:** There is no tool that translates a 2D image into quantifiable physical metric (like exact height in meters or breaking type)

Why the Problem Is Challenging

- Waves change constantly with lighting, angle, wind, and camera quality.
- Key attributes like breaking type and surfability are hard to judge from a single image.
- No existing labeled dataset contains detailed wave attributes.

Idea

- Develop a Computer Vision model that automatically analyzes beach images to extract objective physical parameters (Wave Height, Breaking Type), providing a standardized basis for conditions

Project Definition

SwellSight

Given a single image of ocean waves, use a Multi-Task Deep Learning model to extract objective physical wave parameters.

Input

- One RGB image from a beach camera or a surfer's photograph.

Output

- Wave height: continuous value in meters (Regression).
- Wave type and breaking style: A-frame, closeout, beach break, point break (Classification).
- Wave Direction: left, right, both (Classification).

Project Novelty

- Overcoming the lack of labeled surf data by generating a custom dataset using **Synthetic Depth Maps.**
- This technique allows complete control over wave geometry to train the model with perfect ground-truth labels.
- First model to shift from subjective "quality estimation" to the **precise extraction of physical attributes** from 2D images.
- A unified Deep Learning pipeline that simultaneously solves regression (height) and classification (wave type) tasks for complex fluid dynamics.

Models and methods

Processing Pipeline

- **Synthetic Data Generation:** We create a labeled dataset by generating **Depth Maps** (representing wave geometry) and converting them into photorealistic images using **ControlNet** and Stable Diffusion.
- **Model Inference:** The trained Deep Learning model processes a single 2D image to extract physical wave attributes.

Models & Techniques

- **Data Generation:** Using **Depth Maps** as geometric conditions allows us to create synthetic waves with known, ground-truth physical parameters (Height, Shape)..
- **Wave Analysis Model:** We utilize a **Multi-Task Learning** architecture with shared feature extraction and three specific output heads.

Models and methods

Adjustments & Fine-Tuning

- A pre-trained image encoder is fine-tuned on our custom synthetic dataset. The shared backbone learns robust features relevant for all three tasks simultaneously (geometry, orientation, and scale).

- Domain adaptation: To bridge the gap between synthetic training data and real beach photos, we apply:
  - Aggressive data augmentation (lighting, noise, perspective).
  - Validation against a small set of real-world reference images.

Date specification and generation

Data Requirements

- **Training Set:** A large-scale, fully synthetic dataset generated with precise geometric control.
- **Validation Set:** A small collection of real-world beach images, manually labeled, used solely for **Domain Adaptation** and final testing.

Labeling Strategy:

- **Automatic Ground Truth:** Since we define the wave's geometry (e.g., "Height = 1.8m") *before* generating the image, the labels are inherently 100% accurate. No manual labeling is required for the training set.

Synthetic Data Generation

- **Geometry First:** We programmatically generate **Depth Maps** that define the exact 3D structure of the wave (Height, Shape, Angle).
- **Texture Rendering:** These Depth Maps serve as strict conditions for **ControlNet** (integrated with Stable Diffusion) to generate photorealistic water textures and lighting.

Metrics and KPIs

Measuring Results:

- Performance is evaluated on the model's ability to accurately extract physical attributes from the images.

Quality Assessment per Task:

- Wave Height: Metrics: Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) in meters.
- Wave/Breaking Type:
  Metrics: Accuracy, F1-Score, and Confusion Matrix.
- Wave Direction:
  Metrics: Accuracy and F1-Score.

Evaluation Protocol:

- Synthetic Validation: Testing on a held-out set of synthetic images to verify learning capacity across all three heads.
- Real-World Validation: Running the model on real beach images to assess domain adaptation success and visual consistency.