Mole Scanner

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Problem

SCOPE

Business Objective:

The primary goal of this project is to create a web-based tool for early skin cancer detection, increasing accessibility for individuals who cannot regularly visit dermatologists. The solution could reduce diagnostic delays and improve patient outcomes, aligning with public health objectives to combat skin cancer.

How the Solution Will Be Used:

The trained model will be deployed on a web platform using Gradio and hosted on Hugging Face Spaces. Users will upload an image of a mole, and the model will provide a classification (benign or malignant) with a confidence score.

Existing Solutions:

Current solutions involve in-clinic examinations or mobile apps using proprietary algorithms. While manual examinations are the most reliable, they are costly and time-consuming for frequent monitoring. Mobile apps offer accessibility but often use proprietary "black box" algorithms, raising trust and transparency concerns.

Business Metrics:

Performance Metric: The model must achieve at least 70% accuracy on the test dataset.

Impact Metric:

Successful classification with low latency (<1 second per prediction) to ensure seamless user experience.

Pipeline Overview:

Data Input: Users upload an image through a web interface.

Preprocessing: Images are resized and normalized.

Prediction: The trained neural network classifies the image.

Output:

A prediction label and confidence score are displayed.

Changes in the model or preprocessing pipeline will directly affect the predictions and user confidence in the tool.

Stakeholders:

Users: Patients seeking a quick screening tool.

Healthcare Providers: Dermatologists who might use it as a triage tool.

Developers: Building and maintaining the ML system.

Timeline:

Week 1: Data preparation, exploration, and preprocessing.

Week 2: Model training and evaluation.

Week 3: Hyperparameter tuning and testing.

Week 4: Deployment on Hugging Face Spaces.

Resources:

Computational:

- Kaggle environment for training
- Gradio / Hugging Face Spaces for deployment.

Personnel: 2 developers

Metrics

Minimal "Business Metric" for Success:

The project's success will be defined by achieving a minimum accuracy of 85% in distinguishing malignant from benign moles. This threshold ensures the tool provides meaningful assistance to users, reducing unnecessary anxiety or missed diagnoses.

Additionally, achieving a false-negative rate below 5% is critical since false negatives could lead to undiagnosed malignant cases, which is a major safety concern.

Machine Learning Metrics:

Accuracy: Measures the percentage of correct classifications (malignant or benign). This is directly linked to the business objective of ensuring reliable early detection.

Precision and Recall:

Precision (Positive Predictive Value): Ensures the model does not over-predict malignant cases, reducing false alarms.

Recall (Sensitivity): Ensures the model identifies as many malignant cases as possible, minimizing false negatives.

F1 Score: Combines precision and recall into a single metric to balance false positives and false negatives effectively.

ROC-AUC (Receiver Operating Characteristic - Area Under Curve): Measures the model's ability to discriminate between the two classes (malignant and benign) over various thresholds.

Software and System Metrics:

Latency: The time taken for the system to process an input image and produce a result. The goal is to maintain a latency of less than 2 seconds for user convenience.

Throughput: The number of scans processed per second. This ensures scalability for environments where multiple users might be uploading scans simultaneously.

Model Size: Ensuring the model is lightweight (under 50 MB) to allow easy deployment in web and mobile applications.

Uptime: The deployed system should aim for at least 99% uptime to ensure availability for users.

Connection to Business Objective:

The metrics such as accuracy, precision, and recall directly support the tool's primary goal of assisting in early detection of skin cancer. High precision ensures fewer false positives, reducing unnecessary stress for users, while high recall minimizes the risk of undiagnosed malignancies.

Latency and throughput ensure the solution is user-friendly and scalable, contributing to its usability and adoption as a reliable tool.

DATA

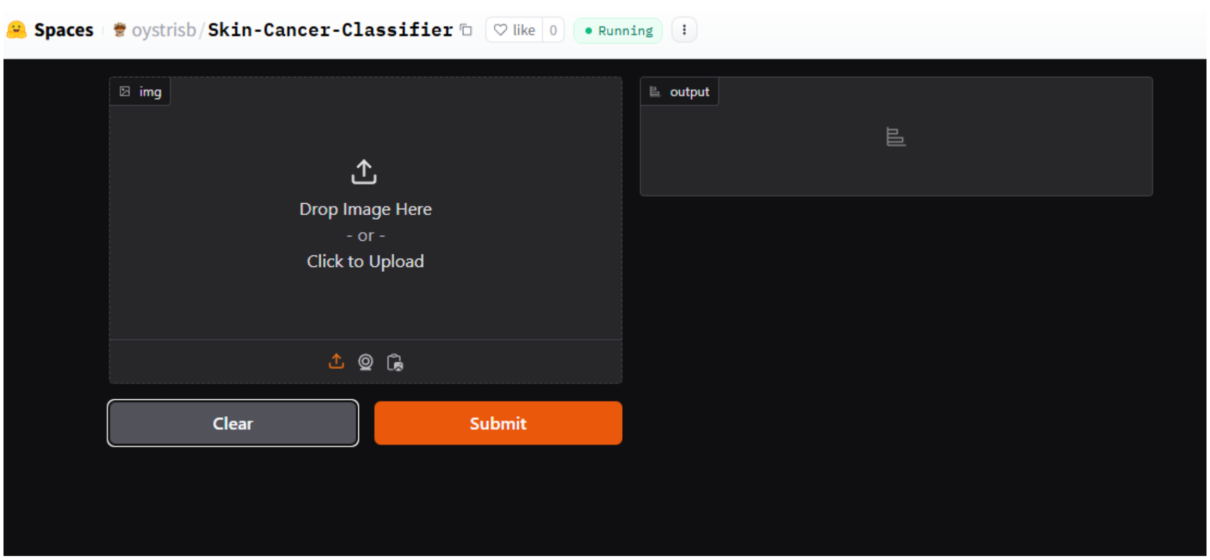
The data we will use are images of moles. These images come from The International Skin Imaging Collaboration (ISIC-archive), which has a large collection of images of various moles. We are using a dataset from Kaggle (Skin Cancer: Malignant vs. Benign) that has been sorted into two labels, 'benign' and 'malignant'. This dataset is balanced with 1800 images in each category. Additionally, all the images are formatted to the same size (224x224), which is something we will also need to do with the images that will be used with the model

MODELING

We are using Artificial Neural Networks to make the model.

DEPLOYMENT

The model will be deployed via Huggingface. The user interface will be built with Gradio and will be simple and user-friendly. The ability to upload images and a simple button to run the model and get a response is all that is needed.



REFERENCES

Dataset: Kaggle Dataset - Skin Cancer: Malignant vs. Benign

Implementation:

- Gradio Interface Tutorial - Hugging Face Spaces Integration.
- TensorFlow Documentation for Neural Networks
- **Curriculum Book**: ***Géron, Aurélien. Hands-On Machine Learning with Scikit-Learn, Keras, and TensorFlow*** (Chapter 10).
- **Community Code**: Example code snippets and visualization methods adapted from other Kaggle projects: Starter: Skin Cancer: Malignant vs. Benign