Detailed Design

Architecture

The architecture that best suits our project is Client-Server.

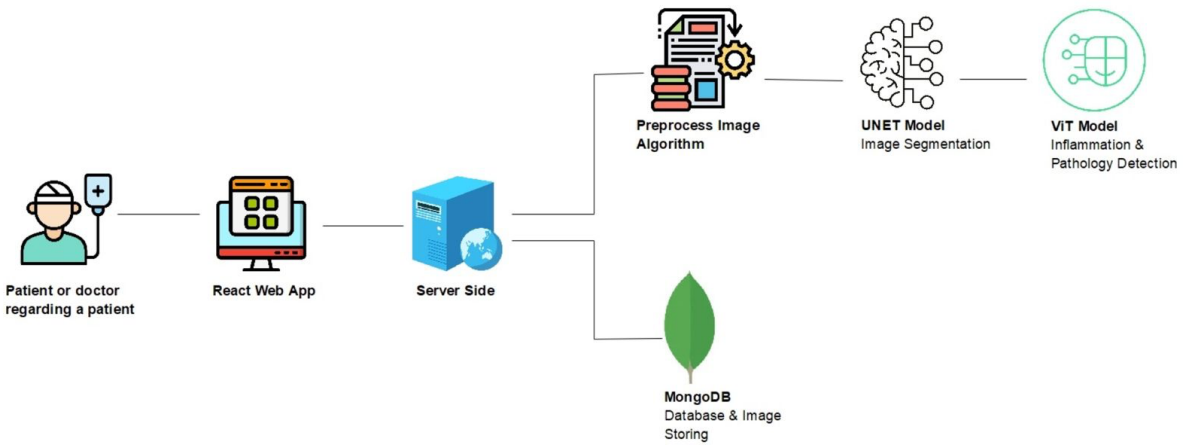
Client-Server Architecture in our project:

- Server:
  - ❖ Manages data and images in a database in MongoDB.
  - ❖ Handles the processing of the images sent from the client.
  - ❖ Send data between the database and the processing model.
- Client:
  - ❖ Uploads images for processing and downloads reports from server.
  - ❖ The client sends his requests through a web app.

Data Storage

- The user's data is stored in JSON.
- Images and trained ML models will be stored in files.
- Image sets' data will be stored in JSON as well.

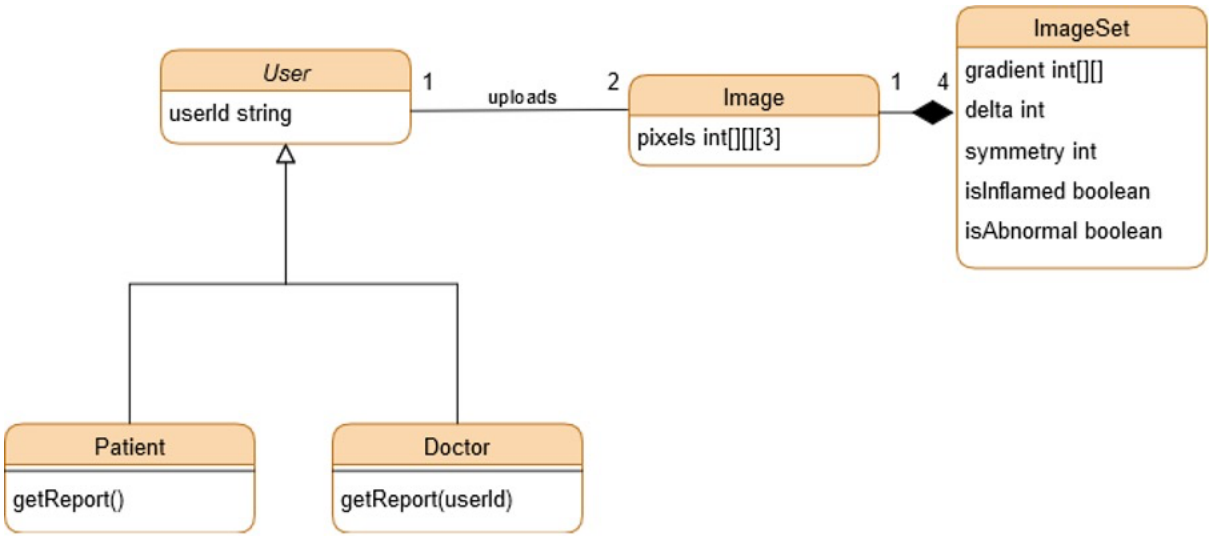
Graphic Description



Data Description

- User – a JSON file that has the following fields:
  - ❖ userID
  - ❖ whether the user is patient or doctor
- Image sets' data – will be saved as JSON with the following fields:
  - ❖ Delta
  - ❖ Gradient
  - ❖ Symmetry
  - ❖ Any other data that we will decide in the future is relevant for the model.

Graphic Description



API specification

- Upload optical and thermal images of hands.
- Download reports based on past images sent to the website.
- Download reports based on userId, if the user is a doctor.
- Display prediction results of the ML model.
- Upload the images to the database for training the model.

Programming languages and tools

We have selected Python for making statistics analysis and for the vast libraries for machine learning. We chose to build our web application using React because of its low learning curve.

Algorithm Description

Non-Machine Learning:

Hand Registering Algorithm:

Algorithm: *To register the hands in the thermal image using the optical image, the algorithm aligns both images through feature-based matching. First, ORB (Oriented FAST and Rotated BRIEF) feature matching is used to detect and match key points between the thermal and optical images. Once matched, a homography transformation aligns the thermal image to the optical image's perspective. This ensures that the thermal image is accurately mapped onto the optical image, preserving anatomical details for further processing.*

Time Complexity: The time complexity of ORB feature matching is O (n + M^2), where is the number pixels in the image and M is the number of keypoints detected, because the complexity of the feature detection is O(n) and the complexity of brute force feature matching is O(M^2). The complexity of the homography transformation is O(KM), M still being the number of keypoints detected and K is the number of iterations the estimation computes, however the K will always be between 100 to 200 and most likely will be hardcoded and that's why it won't increase the complexity. In conclusion, the time complexity will be O (n + M^2), depending either linearly on the number of pixels in the image or exponentially on the number of keypoints detected.

Machine Learning:

1. **Convolutional Neural Network – UNET:**

   Algorithm: *UNet is a CNN architecture designed for image segmentation, especially in medical imaging. It has a U-shaped structure with an encoder that extracts*

features, a bottleneck for deep representations, and a decoder that restores spatial details. Skip connections help retain localization accuracy, making UNet effective for pixel-wise segmentation, even with limited data.

Time Complexity: Since UNet has both a contracting path (downsampling) and an expanding path (upsampling), the overall complexity remains in the order of O(n) per layer, leading to O(D*n) for the full network, where n is the number of pixels in the image and D is the depth of the network.

2. **Transformer – Vision Transformer:**

Algorithm: *The Vision Transformer (ViT) is a deep learning architecture designed for image analysis using self-attention mechanisms instead of traditional convolutional layers. It splits an image into fixed-size patches, flattens them, and embeds them with positional encodings before passing them through a Transformer encoder, originally used in NLP. This allows ViT to model long-range dependencies and global relationships more effectively than CNNs. While ViT requires large datasets for training, it achieves state-of-the-art performance in image classification, segmentation, and object detection, often outperforming CNNs in capturing complex patterns.*

Time Complexity: The time complexity of a Vision Transformer (ViT) is primarily determined by the self-attention mechanism, which operates on image patches.
The dominant computational cost comes from multi-head self-attention (MHSA), which has a complexity of O(M^2 * d), where M is the number of patches and d is the embedding dimension. Unlike CNNs, where complexity scales linearly with image size, ViT's self-attention scales quadratically with the number of patches.

Graphic Description