Literature Review

Machine Learning for Thermal Image Analysis in Detecting Inflammation and Pathology

Introduction

Our project focuses on developing and implementing machine learning algorithms to identify inflammations and pathologies in patients based on thermal images of their hands. This initiative is conducted in collaboration with an ongoing study, **TH-SRG01**, which examines thermal imaging of surgeons' hands. This study, led by Dr. Yair Barzilay and Dr. Lilach Gavish, aims to characterize pain distribution and thermal anomalies in the hands of surgeons, a population known to experience a high tendency for inflammations due to the physical demands of their work. By partnering with this study, we aim to create a practical tool to assist doctors and patients in detecting inflammations more effectively.

The project leverages a unique dataset comprising thermal images of both surgeons and non-surgeon doctors. Surgeons, due to their work, often are inflicted by inflammations in specific hand joints, whereas non-surgeon doctors serve as a control group with minimal or no inflammation. By correlating clinical data with thermal imaging patterns, our machine learning model seeks to provide a reliable, non-invasive diagnostic solution. This collaboration aspires to enhance early detection and monitoring of hand-related pathologies, ultimately improving healthcare outcomes for doctors and patients alike.

Using Machine Learning and Thermal Imaging for Inflammation Detection

The integration of machine learning (ML) with thermal imaging has opened new possibilities in non-invasive diagnostics. Infrared thermal imaging (IRT) has been used to objectively identify acute inflammation in clinical cases involving trauma, vasodilation, and allergy, demonstrating its superiority over subjective measures such as palpation and enhancing diagnostic precision [2].

In addition, ML algorithms have shown promising results in classifying inflammation-related anomalies. For example, Artificial Neural Networks (ANNs) outperformed Support Vector Machines (SVM), achieving a maximum accuracy of 88% in classifying lumbar sympathetic blocks, highlighting ML's reliability in analyzing thermal data and supporting clinical decision-making [1].

Another study validated the use of smartphone-attached thermal cameras for detecting juvenile arthritis, an autoimmune disorder that primarily leads to inflammation in the joints. These devices achieved comparable results to handheld systems, demonstrating high sensitivity (80%) and specificity (84.2%), while also emphasizing the portability and accessibility of IRT, particularly when combined with ML, for telemedicine applications [5].

Focusing specifically on rheumatoid arthritis (RA), a chronic autoimmune disorder affecting the joints, a CNN-based model called RA-XTNet was introduced to leverage thermal imaging and hand radiographs for early diagnosis. This approach achieved an impressive classification accuracy of 93%, showcasing the effectiveness of ML in processing temperature data from small joints to predict inflammation with high specificity and sensitivity [4].

These findings collectively highlight the potential of combining ML with thermal imaging to detect and monitor inflammatory conditions across diverse applications, from occupational health to autoimmune diseases.

Classification Algorithms for Inflammation Detection

Machine learning (ML) algorithms play a critical role in detecting inflammatory conditions using thermal imaging data. Various techniques have been evaluated for their performance and applicability:

1. **Artificial Neural Networks (ANNs):** ANNs have demonstrated superior accuracy and sensitivity in detecting subtle thermal changes compared to simpler models like K-Nearest Neighbors (KNN) and Support Vector Machines (SVM), as shown in the classification of lumbar sympathetic blocks [1].
2. **Convolutional Neural Networks (CNNs):** CNNs excel in analyzing complex image data. For example, the RA-XTNet model achieved a 93% accuracy in detecting rheumatoid arthritis (RA) using thermal images and radiographs, highlighting CNNs' robust feature extraction capabilities [4].
3. **Deep Learning Models with Optimization:** Optimization techniques enhance the performance of deep learning models. A model combining deep convolutional networks with particle swarm optimization (PSO) showed improved accuracy and fewer false positives in detecting rheumatoid nodules [3].
4. **Temperature-Based Algorithms:** Simpler algorithms, such as the within-limb calibration (TAWiC) method, effectively identify inflammation by comparing joint temperatures to control regions. This approach is particularly useful in resource-limited settings due to its simplicity and high sensitivity [5].

These algorithms vary in complexity and applicability depending on the dataset and the specific inflammatory condition. While CNN-based models excel in analyzing feature-rich datasets, simpler approaches like TAWiC are better suited for quick, field-level applications with limited computational resources.

Conclusion

The reviewed literature confirms the technical and clinical viability of our project. Leveraging ML for thermal image analysis can address diagnostic challenges in detecting hand inflammation among surgeons. By building on existing methodologies, our study can fill critical gaps, particularly in developing non-invasive, occupation-specific diagnostic tools.

References

1. **Cañada-Soriano, M., Bovaira, M., García-Vitoria, C., Salvador-Palmer, R., Ortiz de Anda, R. C., Moratal, D., & Priego-Quesada, J. I.** (2023). Application of machine learning algorithms in thermal images for an automatic classification of lumbar sympathetic blocks. *Journal of Thermal Biology, 113*, 103523. https://doi.org/10.1016/j.jtherbio.2023.103523
2. **Ramirez-GarciaLuna, J. L., Rangel-Berridi, K., Bartlett, R., Fraser, R. D. J., & Martinez-Jimenez, M. A.**(2022). Use of infrared thermal imaging for assessing acute inflammatory changes: A case series. *Cureus, 14*(9), e28980. https://doi.org/10.7759/cureus.28980
3. **Dulhare, U. N., & Mubeen, A.** (2023). Detection and classification of rheumatoid nodule using deep learning models. *Procedia Computer Science, 218*, 2401–2410. https://doi.org/10.1016/j.procs.2023.01.215
4. **Kesavapillai, A. R., Aslam, S. M., Umapathy, S., & Almutairi, F.** (2024). RA-XTNet: A novel CNN model to predict rheumatoid arthritis from hand radiographs and thermal images: A comparison with CNN transformer and quantum computing. *Diagnostics, 14*(1911). https://doi.org/10.3390/diagnostics14171911
5. **Balay-Dustrude, E., Bhide, N., Scheck, J., Sullivan, E., Cain, K., Biswas, D., Partridge, S. C., & Zhao, Y.**(2023). Validating within-limb calibrated algorithm using a smartphone-attached infrared thermal camera for detection of arthritis in children. *Journal of Thermal Biology, 111*, 103437. https://doi.org/10.1016/j.jtherbio.2022.103437

Competitors

Feature	Ada Health	Arterys	PathAI	Our Project
Prediction Tool	Symptom checker for general conditions	AI-based diagnosis of major diseases	AI-assisted pathology diagnosis	Specialized in inflammation and pathology detection in hands.
Imagery Based	No, text-based symptom input	Yes, MRI and CT scan	Yes, pathology slides	Yes, thermal imaging analysis
Thermography	No	No	No	Yes, uses thermal images for detection
Target Users	Patients and doctors	Healthcare professionals	Pathologists	Healthcare professionals and also patients with thermal cameras
Pathology Prediction	Limited to general symptom correlation	Focuses on major diseases like cancer and heart disease	Cancer and other major diseases	Focuses on inflammations and pathologies specific to hands
Inflammation Prediction	No	No	No	Yes, specifically in hands
Easy to Use	Yes, user-friendly for general public	No, requires medical expertise	No, for pathologists use only	Yes, user-friendly as long as you have a thermal camera
Real-Time Monitoring	No	No	No	Yes, allowing for immediate inflammation detection and monitoring
Non-Invasive	Yes, symptom-based	Yes, requires advanced imaging but non-invasive to patients	No, invasive sample collection	Yes, uses non-invasive thermal imaging

Ada Health:

Strengths:

- User-Friendly Interface: Ada Health provides a highly accessible, user-friendly platform for both patients and doctors, making symptom checking quick and intuitive.
- Extensive Symptom Database: Ada leverages a broad database of symptoms and conditions, offering comprehensive coverage of general medical conditions.
- Scalability: As a symptom checker, it can be easily scaled to various user groups globally, providing preliminary diagnosis.

Weaknesses:

- Generic Approach: Ada Health is designed to handle a wide range of general symptoms, which may limit its specificity and accuracy in detecting conditions like hand inflammations.
- Lack of Imaging Integration: Ada does not incorporate any imaging data, which is crucial for detecting pathologies.

Arterys:

Strengths:

- Advanced Imaging Techniques: Arterys excels in using cutting-edge AI to analyze complex medical imaging(MRI, CT scans) for diagnosing serious conditions like cancer and heart disease.
- FDA-Approved Solutions: The platform's solutions are FDA-approved, underscoring its reliability and compliance with medical standards.
- Cloud-Based Platform: Arterys offers cloud-based solutions, facilitating real-time collaboration and analysis across different locations.

Weaknesses:

- High Cost and Complexity: The advanced imaging technologies used by Arterys can be expensive and complex, making them less suitable for more accessible and frequent use cases unlike thermal imaging.
- Limited Scope in inflammation Detection: The platform's current focus is on major diseases, lacking the specificity required for detecting hand-related pathologies and inflammations.

PathAI:

Strengths:

- High Precision in Pathology: PathAI offers precise AI-driven analysis of pathology slides, significantly aiding in the diagnosis of diseases like cancer.
- Strong Focus on Diagnostic Accuracy: The platform emphasizes improving diagnostic accuracy and efficiency for pathologists, which is critical for high-stakes medical conditions.
- Collaboration with Healthcare Institutions: PathAI partners with leading healthcare institutions, enhancing its credibility and reach.

Weaknesses:

- Reliance on Pathology Slides: PathAI focuses on traditional pathology slides, which require invasive sample collection.
- Limited to Specific Pathologies: The platform is tailored towards specific diseases like cancer and may not address the broader spectrum of diseases and pathologies.
- No Real-Time Monitoring: PathAI is limited to post-sample analysis.