Project Title:

Seeing Beneath the Surface: Enhancing Diagnostic Accuracy Through Deep Learning-Based Medical Image Analysis

Project Objective:

The objective of this project is to investigate how deep learning models can improve diagnostic accuracy in medical image analysis, with a focus on CT and MRI scans. Specifically, this study aims to evaluate how convolutional neural networks (CNNs) and 3D CNN models extract features, identify abnormalities, and reduce diagnostic errors when compared to traditional image-processing techniques. The project will analyze published datasets and previously validated models to identify performance patterns and highlight the most effective architectural strategies. Ultimately, the goal is to propose a refined framework that could support radiologists by increasing detection accuracy and reducing interpretation time, contributing to ongoing innovation in clinical diagnostic tools.

Project Background and Significance:

Medical imaging plays a foundational role in diagnosing critical conditions such as tumors, cardiovascular disease, neurological disorders, and organ abnormalities. However, interpreting these images is often time-consuming, subject to human variability, and limited by the inherent complexity of CT, MRI, and ultrasound data. Recent advances in deep learning have demonstrated considerable potential for improving diagnostic outcomes by allowing algorithms to identify patterns that may not be apparent to clinicians. Convolutional neural networks (CNNs), 3D CNNs, and hybrid deep learning models have all shown significant promise in research studies between 2016 and 2020, outperforming traditional feature-engineering methods across classification, segmentation, and anomaly-detection tasks.

One core reason deep learning is so impactful in this field is its ability to learn hierarchical features directly from raw imaging data. Rather than relying on manually crafted descriptors, CNNs automatically discover subtle textures, shapes, and spatial relationships that correlate with disease indicators. Studies such as those conducted by Shen et al. (2017) and Litjens et al. (2017) demonstrate that deep learning models can identify complex image features associated with tumors, lesions, and structural abnormalities with high accuracy. Because these models excel at recognizing patterns within high-dimensional data, they are especially effective for MRI and CT imaging, where volumetric information plays a key diagnostic role.

Despite these encouraging findings, the field still faces challenges, most notably issues related to dataset size, variability, generalizability, and clinical integration. For example, models often struggle when trained on limited datasets or when evaluated on images from different institutions or machines. Researchers, including Liu et al. (2019) and Singh et al. (2020), emphasize the need for improved data standardization and better methods for handling noisy or inconsistent medical images. Additionally, clinical adoption is slower than technical progress, partly due to regulatory requirements and the need for models to be interpretable and reliable enough for real-world use.

This project is significant because it synthesizes findings from multiple studies to propose a unified framework for effective deep learning deployment in medical imaging. By clarifying which model architectures, preprocessing steps, and evaluation methods lead to the most reliable results, this research can help guide future development of AI-assisted diagnostic tools. The project will also provide the UCF community with insight into the growing relationship between artificial intelligence and healthcare, an area with considerable societal impact.

Research Methods:

This project will follow a structured research methodology designed to evaluate and synthesize findings on deep learning models used in medical image analysis. Because the project does not involve collecting data directly from human participants, the research will rely on publicly available imaging datasets and previously published peer-reviewed studies. The methodology contains four major steps: (1) dataset selection and preprocessing review, (2) architectural comparison of deep learning models, (3) performance evaluation synthesis, and (4) framework development.

Step 1: Dataset Selection & Preprocessing Review.

The project will begin by examining widely used medical imaging datasets such as BraTS (for brain tumors), LUNA16 (for lung nodules), and NIH ChestX-ray14. The purpose is to understand how dataset characteristics, such as imaging modality, resolution, labeling quality, and sample size, influence model performance. I will document and compare preprocessing techniques such as normalization, augmentation, and ROI extraction used across studies.

Step 2: Architectural Comparison.

Next, I will conduct a comparative analysis of major deep learning architectures, including 2D CNNs, 3D CNNs, U-Net variants, and recurrent/hybrid deep learning systems. This analysis will draw from studies in the 2016–2020 literature review to determine which architectural choices correlate with higher diagnostic accuracy and robustness. Special attention will be given to 3D models, as Singh et al. (2020) highlight their superior ability to capture spatial context in volumetric imaging.

Step 3: Performance Evaluation Synthesis.

I will compile results from multiple peer-reviewed studies to evaluate model performance across metrics such as accuracy, sensitivity, specificity, AUC, and Dice coefficient. This synthesis will help reveal performance patterns across imaging tasks (e.g., segmentation vs. classification) and modalities (MRI vs. CT vs. ultrasound). I will also evaluate the generalizability of models by comparing cross-dataset tests when available.

Step 4: Framework Development.

Using insights from the comparative and performance analyses, I will develop a proposed framework outlining best practices for deploying deep learning models in medical imaging. This framework will include recommendations for preprocessing, architecture selection, training strategies, and evaluation protocols.

Timeline (Summer C: May–August)

- May: Complete deep literature review; organize dataset and architecture notes.
- June: Conduct architectural and dataset comparison analyses.
- July: Perform performance-metric synthesis and begin drafting framework.

- August: Finalize framework, complete written report, and prepare materials for dissemination.

Expected Outcome:

The primary deliverable for this project will be a comprehensive research report summarizing the relationships between dataset characteristics, deep learning model architectures, and diagnostic performance in medical imaging. This report will include a synthesized analysis of existing studies, a refined framework for best practices, and recommendations for future implementation. The report will be written with the intention of submission to the UCF Undergraduate Research Journal. It may also serve as the foundation for a future senior design or graduate-level research project.

In addition to the written report, I plan to produce a poster presentation for UCF's research showcase events. The poster will visually explain deep learning's role in medical image analysis, compare several model architectures, and illustrate examples of diagnostic improvements. This dissemination plan allows the project to reach both technical and non-technical audiences within the UCF community, promoting a broader understanding of AI's impact on healthcare.

The project is expected to generate new insight into which factors most strongly influence the effectiveness of deep learning models in medical imaging. For example, the findings may clarify whether model performance depends more on architecture depth, training strategy, data preprocessing, or dataset variability. This contribution can help guide future researchers in designing more reliable and clinically meaningful AI tools.

For the broader field of artificial intelligence in healthcare, this project will help consolidate information scattered across numerous studies, making it easier for researchers and clinicians to adopt practical deep learning methods. For the UCF community, including future engineers, computer scientists, and biomedical researchers, this project offers a relevant example of how computational methods can meaningfully improve medical decision-making. By strengthening the understanding of AI-driven diagnostics, the project encourages interdisciplinary collaboration and supports UCF's emphasis on innovation in STEM and health-related fields.

Literature Review:

Shen, D., Wu, G., & Suk, H.-I. (2017). Deep learning in medical image analysis. Annual Review of Biomedical Engineering, 19(1), 221–248. https://doi.org/10.1146/annurev-bioeng-071516-044442

Litjens, G., Kooi, T., Bejnordi, B. E., Setio, A. A., Ciompi, F., Ghafoorian, M., van der Laak, J. A. W. M., van Ginneken, B., & Sánchez, C. I. (2017). A survey on Deep Learning in medical image analysis. Medical Image Analysis, 42, 60–88. https://doi.org/10.1016/j.media.2017.07.005

Lee, J.-G., Jun, S., Cho, Y.-W., Lee, H., Kim, G. B., Seo, J. B., & Kim, N. (2017). Deep learning in medical imaging: General overview. Korean Journal of Radiology, 18(4), 570–584. https://doi.org/10.3348/kjr.2017.18.4.570

Ker, J., Wang, L., Rao, J., & Lim, T. (2018). Deep learning applications in medical image analysis. IEEE Access, 6, 9375–9389. https://doi.org/10.1109/ACCESS.2017.2788044

Liu, S., Wang, Y., Yang, X., Lei, B., Liu, L., Li, S. X., Ni, D., & Wang, T. (2019). Deep Learning in Medical Ultrasound Analysis: A review. Engineering, 5(2), 261–275. https://doi.org/10.1016/j.eng.2018.11.020

Singh, S. P., Wang, L., Gupta, S., Goli, H., Padmanabhan, P., & Gulyás, B. (2020). 3D deep learning on medical images: A review. Sensors, 20(18), 5097. https://doi.org/10.3390/s20185097

Preliminary Work and Experience:

My preliminary work for this project includes completing a literature-based annotated bibliography of six peer-reviewed journal articles focused on deep learning for medical image analysis. This initial research helped me identify key models, datasets, and performance trends in the field. Additionally, I have completed coursework in data structures, machine learning fundamentals, computer architecture, and object-oriented programming as part of my computer science major at UCF. These classes have equipped me with strong analytical skills and the foundational knowledge required to understand algorithmic behavior and evaluate computational performance.

I have also worked extensively with coding projects in Python and Java, giving me the technical background needed to analyze and interpret model architectures described in the literature. My involvement as a teaching assistant and my experience developing software tools have strengthened my ability to communicate complex ideas clearly. Together, these experiences demonstrate my capacity to synthesize research findings, evaluate model methodologies, and develop a practical framework for applying deep learning techniques in medical imaging.

IRB/IACUC Statement:

This project does not require IRB or IACUC approval because it involves no human subjects, animal subjects, or direct data collection.

Budget:

Total Budget Requested: $1,485.00

- Cloud GPU Credits – $900
- Data Storage – $180
- Software Tools – $105
- Poster Materials – $150
- Miscellaneous Supplies – $150