**Capstone Project Concept Note and Implementation Plan**

**TransConvNet: Enhancing Kidney Abnormality Detection in CT Imaging through Hybrid Transformer-CNN Model with Integrated Explainability**

**Team Members**

1. MOHAMEDALFATEH TAGALSIR MAROOF SAEED

**Concept Note**

**1. Project Overview**

Abdominal pain constitutes a significant proportion of the reasons for admission to the emergency department. The abdominal cavity contains a diverse range of organ structures, implying a diverse range of disease causes. The first step to diagnosing the pain in the emergency department is radiological imaging. Radiological imaging tests are frequently used to confirm or exclude a suspected condition and to narrow the differential diagnosis list. Advancements in medical imaging technology, particularly in computed tomography (CT), have revolutionized the diagnosis and management of kidney abnormalities. With the growing incidence of renal disorders worldwide, there is an increasing demand for accurate and efficient detection methods. In response to this need, researchers have leveraged the power of deep learning algorithms to develop sophisticated models capable of analyzing CT images for the detection of kidney stones, cysts, tumors, and other anomalies.

The primary aim of this project is to alleviate the workload of healthcare professionals by implementing an accurate classification system for kidney cases across four distinct clinical conditions (Cyst, Normal, Stone, Tumor). By precisely categorizing cases into these clinical conditions, and providing a justification of the decision made, the project endeavors to streamline diagnosis and treatment processes, ultimately contributing to improved patient care and outcomes.

A novel method is proposed: the Hybrid Transformer-CNN Model with Integrated Explainability. This approach leverages the complementary strengths of transformer-based models and convolutional neural networks to enhance classification performance and generalization across diverse datasets. By integrating explainability mechanisms directly into the model architecture, the proposed method ensures transparency and interpretability without relying on external visualization tools.

The project aligns with key United Nations Sustainable Development Goals:

* **Good Health and Well-being (SDG 3**): Improving healthcare outcomes by developing an accurate kidney condition classification system for early intervention.
* **Industry, Innovation, and Infrastructure (SDG 9):** Fostering innovation in healthcare technology with the development of advanced deep learning models.

**2. Objectives**

The project's specific objectives include developing a Hybrid Transformer-CNN Model to accurately classify kidney cases into four clinical conditions: Cyst, Normal, Stone, and Tumor, while integrating explainability for transparent decision-making. Additionally, the model aims to generalize across diverse datasets to ensure robust performance in various clinical settings. Ultimately, the project aims to streamline kidney condition diagnosis in emergency settings, reducing the workload of healthcare professionals and improving patient care outcomes.

In terms of aims and contributions, the project seeks to achieve high accuracy and efficiency in detection and investigating the use of hybrid model while prioritizing explainability and transparency. Its contributions encompass technological advancement in medical imaging, workload reduction for healthcare professionals, enhanced patient care, broad applicability across different datasets, and educational value by elucidating AI-driven diagnostic decisions.

**3. Background**

The global incidence of renal disorders, such as kidney stones, cysts, and tumors, has been on the rise, necessitating accurate and efficient detection methods to improve patient outcomes. Radiological imaging, particularly computed tomography (CT), is crucial in identifying and managing these kidney abnormalities in medical diagnostics. However, the traditional methods of analyzing these images are often time-consuming and reliant on the subjective interpretation of radiologists. This has created a pressing need for the integration of advanced artificial intelligence (AI) techniques to enhance the accuracy and efficiency of kidney abnormality detection [1][2].

Recent advancements in deep learning, especially in convolutional neural networks (CNNs) and transformers, have significantly improved the capabilities of automated diagnostic systems. CNNs have been extensively used for image classification tasks due to their ability to capture spatial hierarchies through convolution operations [3][4][5]. For instance, CNN-based models have achieved notable accuracies of 95% with GrayNet and 91% with ImageNet in urinary stone detection [1] and 96.82% in kidney stone detection using a cross-residual network (XResNet-50) [6]. However, CNNs often struggle with capturing long-range dependencies within the data. On the other hand, transformers, initially developed for natural language processing, have shown remarkable success in handling sequence-to-sequence tasks by focusing on the relationships between different parts of the input data, thereby capturing global context more effectively [7]

**4. Methodology**

This study aims to leverage the complementary strengths of CNNs and transformers by proposing a hybrid transformer-CNN Model with Integrated Explainability named TransConvNet. This unique model is designed to enhance the detection of kidney abnormalities in CT images by combining the local feature extraction capabilities of CNNs with the global context understanding of transformers. Furthermore, integrating explainable AI (XAI) mechanisms directly into the model architecture ensures transparency and interpretability, thereby fostering trust and understanding among clinicians regarding the AI's decision-making process [8].

The proposed TransConvNet model addresses several limitations observed in existing methodologies. For instance, while CNNs have demonstrated high accuracy in detecting kidney abnormalities, their performance can vary significantly across different datasets and imaging protocols [9][10][11]. A study utilizing the "CT KIDNEY DATASET: Normal-Cyst-Tumor and Stone" reported the Swin Transformer achieving an impressive accuracy of 99.30% [3]. Other models like YOLOv7 have also shown high performance with a mean Average Precision (mAP50) of 85%, precision of 88.2%, sensitivity of 82.9%, and an F1 score of 85.4%. However, the lack of interpretability in AI models poses a challenge in clinical settings where understanding the rationale behind a model's prediction is crucial for treatment decisions [8]. By incorporating XAI techniques, TransConvNet improves diagnostic accuracy and provides detailed explanations for each prediction, enhancing the system's overall reliability. These results highlight the potential of TransConvNet to improve patient care and outcomes significantly [8].

**5.** **Architecture Design Diagram**

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*Fig 1: Hybrid Model Diagram*

As shown in Fig 1, our model is designed to classify kidney CT images into four conditions: cyst, normal, tumor, and stone. It begins by inputting the CT image into a series of Convolutional Neural Network (CNN) layers that extract essential features. These features are then reshaped and processed through multi-head attention layers, which focus on different regions of the image to capture relevant relationships. The output is reshaped again and passed through an additional CNN layer to enhance pattern recognition. A flatten layer converts the multi-dimensional output into a one-dimensional vector, which is fed into dense layers for the final classification. To ensure transparency and interpretability, we employ Grad-CAM (Gradient-weighted Class Activation Mapping) to highlight the important regions in the image that influenced the model's decision.

**6. Data Sources**

## The primary dataset (CT KIDNEY DATASET: Normal-Cyst-Tumor and Stone) consists of 12,446 CT scan images categorized into four classes. Table 1 presents the distribution of image categories in the CT Kidney Dataset, while Figure 1 illustrates sample images from the dataset. The additional dataset (Kidney Stone Detection Dataset) comprised 433 subjects: 278 with kidney stones (790 images) and 165 without stones (1009 images). Subjects used for training and validation were different from those used for testing to avoid bias.

A close-up of an x-ray

Description automatically generatedAn x-ray of a body

Description automatically generatedA close-up of an x-ray

Description automatically generatedA close-up of an x-ray

Description automatically generated

***Cyst Normal Stone Tumor***

**Figure 2: CT KIDNEY DATASET Sample**

**Table 1: Distribution of Images in the CT Kidney Dataset**

|  |  |
| --- | --- |
| Category | Number of Images |
| Cyst | 3,709 |
| Normal | 5,077 |
| Stone | 1,377 |
| Tumor | 2,283 |

**7. Literature Review**

Abdominal pain is a common reason for emergency department admissions, with diverse organ structures in the abdominal cavity leading to various disease causes. Radiological imaging, particularly computed tomography (CT), is essential for diagnosing and managing kidney abnormalities. The increasing global incidence of renal disorders has driven the demand for accurate detection methods, prompting researchers to leverage deep learning algorithms. Several studies have proposed different AI models for detecting kidney stones, cysts, tumors, and other anomalies in CT images. Notable approaches include Parakh et al.'s cascade CNN model, achieving 95% accuracy with GrayNet, and a cross-residual network (XResNet-50) reaching 96.82% accuracy. Another significant contribution is the "CT KIDNEY DATASET: Normal-Cyst-Tumor and Stone," used to evaluate various models, with the Swin Transformer achieving 99.30% accuracy. Other studies employed YOLO architectures and CNN-based hybrid models, achieving high accuracies and demonstrating the potential of AI in kidney abnormality detection. Despite these advancements, limitations in generalization across different imaging protocols and patient demographics persist, leading to the proposal of a Hybrid Transformer-CNN Model with Integrated Explainability to enhance performance and interpretability.

**Implementation Plan**

**1. Technology Stack**

In this project, a robust and comprehensive technology stack will be utilized to build, train, test, and deploy the model. The primary programming language will be Python, chosen for its extensive support for machine learning and deep learning libraries, as well as its versatility and ease of use. The TensorFlow framework will be employed to implement the Hybrid Transformer-CNN model, leveraging its powerful capabilities for building and deploying deep learning models. Several other libraries will also be integral to the project, providing essential functions for data manipulation, numerical computations, and visualization.

**Programming Languages:**

* **Python:** The main programming language for developing the entire pipeline, from data preprocessing to model deployment.

**Libraries:**

* **TensorFlow:** The primary framework for developing and training the Hybrid Transformer-CNN model, known for its flexibility and scalability in deep learning applications.
* **Keras:** An API within TensorFlow that simplifies the creation and training of neural networks.
* **Pandas:** Used for data manipulation and analysis, providing data structures and functions needed to work with structured data efficiently.
* **NumPy:** Fundamental for numerical computations, offering support for large, multi-dimensional arrays and matrices, along with a collection of mathematical functions.
* **Matplotlib:** Utilized for creating static, interactive, and animated visualizations to understand data distributions and model performance.
* **Scikit-learn:** Essential for implementing and evaluating machine learning models and preprocessing techniques.
* **OpenCV:** For image processing tasks, aiding in the preprocessing of CT images.
* **Pillow:** Another library for image processing, which will be used for image augmentation techniques.

**Frameworks:**

* **TensorFlow:** As mentioned, this will be the core framework for developing deep learning models, supporting both CNN and Transformer architectures.
* **Flask or Django:** For deploying the trained model as a web application, allowing for real-time predictions and user interactions.
* **Apache Airflow:** For workflow management, ensuring smooth automation and scheduling of data preprocessing, training, and evaluation tasks.

**Other Software Components:**

* **Jupyter Notebook:** An interactive environment for developing and testing the code, allowing for exploratory data analysis and iterative model development.
* **Docker:** To containerize the application, ensuring consistency across different environments and simplifying the deployment process.
* **Git:** For version control, facilitating collaboration and tracking changes in the codebase.

1. **Timeline**

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| --- | --- | --- |
| Stage | Week | Task |
| Data Collection and Preprocessing | **Week 1** | Collect CT images from available datasets (e.g., EMSC, Kandilli Observatory, USGS, NASA EOSDIS). |
|  | **Week 2** | Clean the CT images. |
|  |  | Perform data augmentation to increase the dataset size and variability. |
|  |  | Preprocess images (resizing, normalization, etc.). |
| Model Development | **Week 3** | Design the architecture for the Hybrid Transformer-CNN model. |
|  |  | Implement the model architecture in TensorFlow/Keras. |
|  | **Week 3** | Code the model, including the integration of explainability mechanisms. |
|  |  | Set up data loaders and preprocessing pipelines in TensorFlow. |
| Training and Evaluation | **Week 4** | Train the model on the preprocessed dataset. |
|  |  | Monitor training progress and adjust hyperparameters as needed. |
|  | **Week 4** | Evaluate the model on a separate validation dataset. |
|  |  | Analyze metrics (accuracy, precision, recall, F1 score) and generate performance reports. |
| Deployment | **Week 5** | Optimize the model for deployment (e.g., quantization, pruning). |
|  |  | Test the optimized model to ensure no significant loss in accuracy. |
|  | **Week 5** | Develop a web application using Flask or Django to deploy the model. |
|  |  | Conduct final testing of the deployed model. |

**3. Milestones**

No milestones yet.

**4. Challenges and Mitigations**

With the dataset prepared, the focus shifts to effectively leveraging AI for kidney disease classification while addressing key challenges. Despite having a ready dataset, ensuring its quality, diversity, and balance remains critical for training robust models. This involves careful preprocessing, including handling missing data and standardizing features, to optimize model performance. Additionally, employing advanced AI techniques such as deep learning and ensemble methods can enhance classification accuracy by effectively capturing complex patterns across diverse patient data. Model interpretability remains pivotal, facilitating trust and usability in clinical settings. Rigorous validation using cross-validation and external datasets validates model generalizability, crucial for real-world application. Ethical considerations, including data privacy and fairness, are paramount throughout the process. Collaborating with domain experts ensures clinical relevance and alignment with healthcare practices, ultimately paving the way for impactful AI-driven advancements in kidney disease classification.

**5. Ethical Considerations**

There are no ethical considerations in our project

**6. References**

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