[Slide 1: 50s]

Hello and welcome. I'm delighted to have the opportunity to share with you the research proposal on the topic 'Deep Learning-Based Synthetic Computed Tomography Generation in Radiotherapy.' My name is Nithya Kanakavelu, and I'm currently pursuing my Master's in Artificial Intelligence.

I'll be presenting my research proposal, which is a significant component of the M.Sc. program. This research serves as one of the summative assessments for the module 'Research Methods and Professional Practice.'

The research explores the exciting realm of deep learning and its application in generating synthetic computed tomography images, a topic that holds great promise in the field of radiotherapy.

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In the context of Head and Neck Radiotherapy, the standard care of treatment is to deliver the prescribed radiation dose in 6 to 7 weeks as fractionated dose (Grégoire et al., 2015)

Treatment planning computed tomography CT images is paramount for the accuracy of planning and dosage calculations. The challenge arises from the dynamic nature of tumour and anatomical changes during the 6 to 7 weeks course of treatment. To ensure the initial treatment plan remains resilient to these changes, daily imaging using Cone Beam Computed Tomography CBCT is employed (Van Kranen et al., 2013).

However, there's a catch. The dosimetric accuracy of CBCT for recalculations is suboptimal, presenting a roadblock in achieving the precision required for effective radiotherapy. To compound the issue, repeated CT scans, while providing better accuracy, come at the cost of additional radiation dose to the patient (Bell et al., 2018).

Herein lies the research problem: the pressing need for a reliable method to generate synthetic CT images from re-using existing daily CBCT acquired for treatment verification (Spadea et al., 2021). This would revolutionise radiotherapy planning by enhancing accuracy and safety without subjecting the patient to unnecessary doses of radiation. This research aims to bridge this gap by proposing a novel solution.

The goal is the development of a deep learning-based approach to generate synthetic CT images. By utilising the power of artificial intelligence, create a tool that can accurately mimic CT images from the available CBCT data.

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So the compelling research question is: Is it possible to influence the power of deep learning methods to efficiently generate synthetic CT images from CBCT within the realm of head and neck radiotherapy? And, more importantly, can these artificial images attain the level of precision required for effective treatment planning?

The journey in this research proposal revolves around these questions, as we explore the transformative potential of deep learning in enhancing the accuracy and safety of radiotherapy

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This research has two primary goals, each with a set of specific objectives.

Goal 1: The first goal is to create a robust Deep Learning Model for Generating Synthetic CT Images. To achieve this, I have outlined the following objectives:

Objective 1.1: The initial objective is to gather and prepare a diverse dataset comprising CBCT images along with their corresponding CT images. This is crucial as the quality of the dataset forms the foundation of the research.

Objective 1.2: Building upon the dataset, will deploy and train a deep neural network architecture that is specifically tailored for the generation of synthetic CT images. This model, often referred to as a convolutional neural network, will play a pivotal role in the research.

Objective 1.3: In order to validate the model's effectiveness, need to evaluate its performance through a combination of quantitative and qualitative assessments. This comprehensive approach ensures that a full understanding of how well the model is performing.

Goal 2: The second goal centers on Evaluating the Clinical Effectiveness and Precision of Synthetic CT Images in Radiotherapy Planning.

Objective 2.1: The initial objective here is to conduct a comparative analysis between synthetic CT images and real CT images. The primary focus will be on assessing anatomical precision to ensure that the synthetic images are accurate and reliable.

Objective 2.2: Moving forward, investigate the influence of synthetic CT images on radiotherapy planning and the accuracy of dose calculations. This step is essential in understanding how well the synthetic images can be integrated into practical clinical applications.

Objective 2.3: Finally, will scrutinise the practicality and safety of incorporating synthetic CT images into patient treatment. This is a crucial aspect of the research as it assesses the real-world applicability and patient-centered outcomes.

[Slide 5:65s]

As seen in this slide, several authors had previously studied the utilisation of synthetic CT generation from CBCT images on various sites like head and neck, nasopharynx, lung, breast, abdomen and Thorax. Also many studies have been conducted to utilise deep learning methods to enhance the image quality of CBCT images and also in generating missing anatomy due to the limited field of view in the CBCT images. The common algorithms used were eCNN, U-NET, GAN module, V-Net, ResNet, cycleGAN. This has been successfully applied for adaptive radiotherapy accounting the tissue changes during the radiotherapy course. There is a vacant area awaiting research to find best model for head and neck treatment site.

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This research project is designed as conclusive research, which means that the aim to draw clear and definitive conclusions from this study. To achieve this, I've adopted a mixed methodology, incorporating both qualitative and quantitative approaches. This enables to gather a comprehensive and well-rounded understanding of the research problem.

In terms of data gathering, an approach by combining both quantitative and qualitative observations will be used, carefully assembling a diverse dataset, which includes paired CBCT and CT images from previous patients. This dataset serves as the foundation for the research.

Moving forward, data preparation is of utmost importance, to undertake the task of standardising and preprocessing the dataset. This involves various essential steps, including image registration and segmentation. The goal is to ensure that the data is consistent, accurate, and ready for analysis.

The heart of the research lies in the deep learning architecture to develop a sophisticated deep neural network model, specifically a convolutional neural network (CNN). This model is instrumental in generating synthetic CT images, a crucial component in the study.

The model doesn't stop at creation; it needs to be trained and validated.. To assess its performance, apply metrics like mean squared error and the structural similarity index.

A pivotal aspect of the research is the clinical assessment, examining the practicality of synthetic CT images in radiotherapy planning. This examination takes the form of a comparative study with authentic CT images to ensure the viability and accuracy of the synthetic images.

Finally, to fully commit to ethical standards, follow ethical clearance, a vital step to ensure the responsible and compliant use of patient data. This ensures that the research adhere to all data protection regulations, and patient privacy remains a top priority.

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In this project, as mentioned I hold the utmost regard for patient data privacy and confidentiality. Hence committed to seeking ethical approval to ensure that all patient data is handled with the utmost care and in compliance with stringent privacy standards.

Now, as with any research endeavor, there are inherent risks. In this case, these risks primarily revolve around the potential for errors in the generation of synthetic CT images, which could have implications for treatment planning. To address this, implement a comprehensive risk mitigation strategy that includes rigorous validation processes and thorough clinical assessments.

Additionally, transparency and respect for the individuals who entrust us with their data would be priortised. To ensure this, informed consent will be carefully obtained for the use of patient data, further safeguarding their rights and privacy throughout the research journey.

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The central achievement of this project is the development of a deep learning model, specifically utilising a cycle-consistent generative adversarial network This model will be engineered to have the remarkable ability to generate synthetic CT images from CBCT data.

The data for training and evaluation will be split into three parts: Training (80%), Testing (10%), and Validation (10%). This separation is crucial for training the model effectively and assessing its performance accurately.

The training process involves various steps, including designing the generator and discriminator networks. These networks play a crucial role in the GAN framework for generating and assessing the quality of synthetic images.

Loss functions will be defined to guide the training process. These functions measure the dissimilarity between the generated images and real CT images, helping the model improve over time.

The model will be trained using the training dataset, and hyperparameter tuning may be performed to optimise the model's performance.

After training, the model will undergo an evaluation process. This phase assesses how well the model has learned to generate synthetic CT images by comparing the generated images to the real CT images from the testing dataset.

Post-processing steps may be applied to refine the synthetic images further. These steps aim to improve the quality, accuracy, and clinical relevance of the generated CT images.

Once the model is thoroughly developed and evaluated, it may be deployed in a clinical setting or a research environment for practical use.

A detailed report will be created to document the entire research project. This report will provide an in-depth exploration of the model's development, evaluation process, and findings. It may also discuss the potential impact of synthetic CT images on radiotherapy planning.

[Slide 9:88s]

In Month 1, the primarily focus will be on data collection and the initial stages of data preprocessing to ensure that I have a robust dataset to work with.

Moving into Months 1 and 2, the core activity will be model development and training. This intensive two-month period is dedicated to building the deep learning model for synthetic CT image generation, a critical phase of the research.

In Month 3, I will transition to model validation and performance evaluation. This phase involves rigorously testing and assessing the model's effectiveness and accuracy.

By Month 4, will be engaging in clinical assessment and initiating the ethical approval application process, where I will ensure that the research meets the highest standards of ethics and safety.

Months 4 and 5 will be dedicated to the final analysis of the findings and the comprehensive report writing. This phase involves synthesising all the data, results, and insights gathered throughout the research.

Finally, in Months 5 and 6, I will focus on the dissemination of my research findings and the potential publication of the work.

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