CHAPTER I
INTRODUCTION

1.1. Background

In the human body, old cells naturally die and are replaced by new ones as part of the normal cell regeneration process. However, when a group of abnormal cells undergoes excessive and uncontrolled division, they may continue to grow and spread beyond the body's normal regulatory mechanisms, eventually forming a mass of tissue known as a tumor [1]. Across the globe, lung cancer claims more lives than any other variety of cancer. Detecting this disease quickly and precisely is critical to give patients a better chance at effective treatment and survival. Lately, medical professionals have turned more to machine learning because it can process vast quantities of medical data very quickly. As a result, it has become a valuable tool for supporting the identifying cancer at an early stage [2]. In Indonesia, lung cancer stands out as one of the most regularly detected types of cancer. Furthermore, statistics from the World Health Organization (WHO) indicate that no other cancer variety claims as many lives across the nation [3].

Histopathological images are a type of medical image obtained through microscopic examination of tissue samples collected during a biopsy procedure. These images enable pathologists to examine tissue characteristics at the cellular level, including the structure of the nucleus, cytoplasm, and the overall arrangement of cells and tissues. By providing detailed visualization of these features, histopathological images allow morphological changes associated with tumor development to be identified more clearly, making them an essential standard for the evaluation and diagnosis of various types of cancer [4].

With the increasing incidence of lung cancer, automating the evaluation of histopathological images has grown much more vital. Having pathologists review slides manually takes a lot of time and often causes eye strain, which may reduce diagnostic accuracy. Deep learning–based systems can assist by providing fast and objective preliminary predictions, thereby supporting large-scale diagnostic workflows. Nevertheless, the performance of these models is heavily contingent on how well they can retrieve both fine-grained local details and overarching global configurations within complicated tissue formations [5].

As artificial intelligence (AI) progresses rapidly, medical experts rely more on deep learning methods to assist in diagnosing different illnesses, such as lung cancer. The Shifted Window Transformer (Swin Transformer) stands out as a highly effective deep learning architecture for examining medical imagery. This Transformer-based model utilizes a window-based self-attention mechanism alongside systematically shifted windows, allowing the system to gather detailed local details and broad regional context quite easily. Because of its hierarchical setup, the framework can build multi-scale feature representations step by step, which makes it ideal for processing high-resolution medical scans like histopathological slides. Traditional frameworks like Convolutional Neural Networks (CNNs) depend on rigid convolutional kernels in contrast, the Swin Transformer offers much better flexibility when mapping spatial connections between image patches, creating a strong opportunity to raise the accuracy of lung cancer categorization using histopathological images [6].

Research named "*Classification of Mobile-Based Oral Cancer Images Using the Vision Transformer and the Swin Transformer*" (2024) proved that the Vision Transformer (ViT) and Swin Transformer can both categorize medical images with high accuracy. In this study, ViT breaks images down into smaller segments and uses a self-attention setup to understand how these distant pieces relate to one another. In contrast, the Swin Transformer incorporates a multi-tiered architecture paired with a shifted-window approach. This specific design significantly accelerates visual feature extraction while lowering overall processing overhead [7]. Furthermore, the study entitled *"Efficient Lung Cancer Image Classification and Segmentation Algorithm Based on an Improved Swin Transformer"* confirmed how well the Swin Transformer setup works when sorting lung cancer cases from patient scans. The tool utilizes a multi-layered configuration alongside a shifted window self-attention approach. Through this method, it successfully extracts both fine-grained and overarching features while minimizing resource consumption. Tests indicated that this new strategy performed just as well as, or better than, alternative options like the ViT and frameworks built on CNNs. Such outcomes point to the Swin Transformer as a highly capable choice for analyzing lung cancer imagery analysis and further support its that application to histopathological image classification [8].

Methods driven by deep learning show excellent promise in analyzing of histopathological images with high accuracy. Out of the frameworks built to evaluate medical scans, the Shifted Window Transformer (Swin Transformer) stands out as a highly capable option, especially when sorting lung cancer cases. This architecture aims to overcome the drawbacks of human evaluation, which depends heavily on the personal skill of pathologists and often creates inter-observer variability. The ability to capture both localized details and broad structural layouts makes the Swin Transformer perfectly suited for investigating complex tissue formations in high-resolution histopathology. This capability is driven by its hierarchical shifted window self-attention framework.

This project focuses on applying and testing how well the Swin Transformer works for classifying lung cancer using histopathological imagery. This new setup wants to raise the accuracy, precision, and consistency of the categorization, creating a much more objective and streamlined workflow for lung cancer diagnosis. Providing a fast and dependable means for early diagnosis is the primary goal of this research. By advancing AI-based systems for detecting lung cancer, this work is expected to offer valuable support to medical practitioners.

1.2. Problem Formulation

Considering the background points raised earlier, this investigation explores the following research questions:

1. How can the Swin Transformer be deployed to categorize lung cancer using histopathological slides?
2. How well does the Swin Transformer perform when sorting lung cancer cases according to evaluation metrics like accuracy, precision, and recall?

1.3. Research Objectives

Driven by the research questions stated earlier, the goals of this project are listed below:

1. To deploy the Swin Transformer model for classifying lung cancer cases through histopathological imagery.

2. To evaluate the overall capability of the Swin Transformer framework using specific evaluation metrics like accuracy, precision, and recall.

1.4. Research Benefits

This project aims to offer valuable theoretical insights alongside practical applications, which are detailed below:

1. Theoretical Contribution

   This research looks to expand the current academic literature regarding how the Swin Transformer operates within medical image analysis, especially concerning lung cancer categorization using histopathological slides. These outcomes could act as a useful foundation for subsequent projects focused on creating advanced deep learning approaches for lung cancer classification.

2. Practical Contribution

   This investigation aims to deliver actionable guidance for clinicians and medical centers trying to leverage AI to assist in lung cancer diagnosis. By employing a Swin Transformer–based classification system, the analysis of histopathological images can be performed more quickly, accurately, and efficiently, thereby improving the quality and consistency of diagnostic outcomes.

1.5. Research Limitations

To guarantee that the investigation maintains a clear focus and stays within its boundaries, the following limitations are established:

1. This study utilizes secondary data from the LC25000 (Lung and Colon Cancer Histopathological Images) dataset, which was sourced from its official paper on arXiv (https://arxiv.org/abs/1912.12142v1). Our focus is confined strictly to the lung compartment of the dataset, totaling 15,000 images. These images are categorized into three distinct pathological groups: Lung Benign Tissue, Lung Adenocarcinoma, and Lung Squamous Cell Carcinoma.
2. This project concentrates solely on sorting lung cancer cases through histopathological imagery and omits any other forms of malignancies.

3. The deep learning framework selected for this investigation remains restricted to the Swin Transformer.
4. The boundaries of this research cover data preprocessing, model training, performance evaluation, along with deploying the finished framework inside a web-based system. Testing the system in a clinical setting or launching it for live medical use falls outside these research boundaries.
5. The overall capability of the designed system undergoes testing through standard classification metrics, namely accuracy, precision, and recall.

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