CHAPTER I
INTRODUCTION

1.1. Background of the Study

Tinea Capitis is a contagious skin disease caused by Dermatophyte fungal infections on the human scalp, emerging as a serious global health problem with a prevalence rate among children worldwide reaching 7% to 33% [1]. The spread rate of this disease varies significantly across demographics, with extreme figures in the African continent reaching 81.2% in Mathare, as well as in the Asian continent, such as India, touching 51.3% [1]. In Indonesia itself, the cases of Dermatophytosis infection rank second highest at 52%, where the prevalence of Tinea Capitis at RSUD Dr. Soetomo Surabaya reached 7.2% in 2016 for the 5–14 years age group, and reached 27.8% at RSUD Dr. Pirngadi Medan for the 5–11 years age group [2]. Specific clinical variations are also recorded in the medical record data at RSUD Deli Serdang, where male patients statistically dominate at 54.1% compared to female patients at 45.9%, with the most frequent patient age range being 1–10 years at 32.4% [1]. The high prevalence rate and the broad demographic spectrum of these patients underscore the urgent need for rapid and accurate medical treatment to break the chain of infection transmission.

In the practice of medical treatment in the field, the diagnosis of Tinea Capitis skin disease at the primary healthcare facilities is confronted with various clinical obstacles that trigger errors and ambiguity in handling. The primary obstacle is the highly cost of digital dermoscopic tools and equipments, which restricts primary healthcare facilities to relying solely on conventional visual observation [3]. Such manual visual observation gives rise to a secondary challenge, namely the high vulnerability to diagnostic errors due to interpretive bias and subjectivity among the medical personnel on duty [4]. These diagnostic challenges become increasingly complex due to the identical visual similarities between inflammatory and non-inflammatory subtypes [5]. Errors in visually distinguishing these disease subtypes carry a high risk of causing medication incompatibility, delays in medical therapy, and even triggering permanent alopecia in patients.

To overcome the limitations of conventional visual diagnosis methods, Deep Learning-based computer vision technology has emerged as an intelligent solution; however, field facts indicate that the implementation of Deep Learning is frequently constrained by the problem of class imbalance in data distribution. This technical phenomenon reflects the real epidemiological conditions in the field, where certain disease subtypes possess a sample prevalence that far exceeds other rare subtypes, thereby forming majority and minority classification classes, which potentially triggers architectural model prediction bias towards the majority classification class. To mitigate this dataset statistical asymmetry, pre-processing intervention of dermoscopic medical image data through image augmentation techniques becomes an absolutely necessary methodological step in this research. Through a series of synthetic manipulation transformations such as geometric rotation, orientation flipping, and brightness intensity adjustment, the quantity and variability of the training data in the minority classes can be artificially balanced. It is this balanced proportion of data presentation that compels the Deep Learning architectural models to proportionally learn the diagnostic feature representations of each subtype.

In the domain of medical image recognition, the Convolutional Neural Network (CNN) architectures such as ResNet-50 and EfficientNet-B2 have been proven to possess superior feature extraction capabilities. The superiority of the ResNet-50 model, which is capable of overcoming the vanishing gradient problem through its Residual Block feature, has been empirically proven in research related to fashion product image classification, where the model successfully achieved a testing accuracy rate of 97.83% [6]. Meanwhile, the Compound Scaling method in the EfficientNet-B2 model has also been validated through human skin disease classification research, successfully obtaining a performance percentage of 84.0% for accuracy, 85.0% for precision, 83.0% for recall, and 84.0% for F1-score [7]. The unique computational characteristics of these two CNN models offer a level of efficiency that is highly relevant to resolving the complexity of visual patterns in Tinea Capitis lesion images. The utilization of these high-performance architectures is expected to automate the recognition of complex skin disease patterns that are difficult to discern by the naked human eye.

Although the single Convolutional Neural Networks architectural models exhibit promising performance, their utilization frequently encounters narrow generalization boundaries when faced with fluctuating variations in the resolution and lighting of medical images. Therefore, the Soft Voting Ensemble Learning paradigm is introduced as a resolutive approach to simultaneously combine the predictive feature extraction capabilities of the ResNet-50 and EfficientNet-B2 models. This ensemble approach operates by aggregating the classification class probability values from several independent architectural models to generate a final diagnostic decision that is significantly more consistent, stable, and reliable. However, determining the proportional contribution weights for each architecture requires a mathematical hyperparameter optimization strategy, rather than mere subjective manual adjustments. Through a comparative analysis between the deterministic search method (Grid Search) conducted in sequential iterations and the stochastic search method (Random Search) conducted in random iterations, this research endeavors to discover the most optimal combination of contribution weights to maximize the fusion performance of the ensemble model.

Based on all these urgencies and theoretical foundations, this research proposes scientific novelty through the integrative combination of the individual ResNet-50 and EfficientNet-B2 architectural models using Soft Voting Ensemble Learning paradigm to computationally classify Tinea Capitis subtype images. The objective of engineering this artificial intelligence architecture is to facilitate rapid and precise initial clinical diagnosis enforcement in order to prevent subsequent medical treatment complications in patients as well as transmission from infected patients to the surrounding community. To bridge the complexity of algorithms with practical needs of medical personnel working in field, the best architectural model from this research will be implemented into a website-based Clinical Decision Support System interface. This Clinical Decision Support System is engineered modernly utilizing the Laravel 12 framework on the backend side, Tailwind CSS on the frontend side, and MySQL on the Relational Database Management System side, so as to create a responsive Computer-Aided Diagnosis tool that is ready to be utilized by public healthcare facilities.

1.2. Problem Formulation

Based on the research background and the problems elaborated in detail in the previous section, the author formulates the following research problems:

1. How can a classification architectural model for Tinea Capitis skin disease be developed using Soft Voting Ensemble Learning by combining the ResNet-50 and EfficientNet-B2 architectural models?
2. How does the performance of proposed Soft Voting Ensemble Learning architectural model compare to the performance of the individual single architectural models (ResNet-50 and EfficientNet-B2) in classifying Tinea Capitis disease subtypes?
3. How do variations in dataset splitting scenarios of Tinea Capitis medical images affect the accuracy and stability of the architectural model in recognizing the Tinea Capitis subtypes, in order to determine the most optimal configuration of training, validation, and testing data ratios?
4. How do the deterministic Grid Search and the stochastic Random Search optimization methods and techniques compare in terms of effectiveness and efficiency when determining the optimal combination of contribution weights within the Soft Voting Ensemble Learning paradigm?
5. How can the best classification architectural model be implemented into a website based interface system using the Laravel 12 framework and the Tailwind CSS to facilitate clinical diagnosis?

1.3. Research Objectives

Based on the problem formulation elaborated in detail in the previous section, the main objectives of conducting this research are as follows:

1. To develop a classification architectural model for Tinea Capitis skin disease using Soft Voting Ensemble Learning by combining the ResNet-50 and EfficientNet-B2 architectural models.
2. To compare the performance of proposed Soft Voting Ensemble Learning architectural model in classifying Tinea Capitis disease subtypes with the performance of the individual single architectural models (ResNet-50 and EfficientNet-B2).

3. To analyze the effect of variations in the dataset splitting scenarios of Tinea Capitis medical images on the accuracy and stability of the architectural model in recognizing Tinea Capitis subtypes, in order to determine the most optimal configuration of training, validation, and testing data ratios.
4. To compare the effectiveness and efficiency of the deterministic Grid Search and the stochastic Random Search optimization methods and techniques in determining the optimal combination of contribution weights within the Soft Voting Ensemble Learning paradigm.
5. To implement the best classification architectural model into a website based interface system using the Laravel 12 framework and Tailwind CSS to facilitate clinical diagnosis.

1.4. Significance of the Study

With the completion of this thesis research, it is expected to yield various theoretical and practical benefits, including:

1. Providing a tangible research contribution to the development of deep learning based on ensemble learning for medical image-based visual data classification processes, particularly for Tinea Capitis disease.
2. Serving as a reference for future research regarding the development of the Soft Voting Ensemble Learning paradigm using the Convolutional Neural Network architectural models, such as Residual Network and EfficientNet, to be applied in medical image-based visual data classification tasks for other diseases.
3. Providing empirical insights into the comparative effectiveness between deterministic weights optimization methods (Grid Search) and stochastic weights optimization methods (Random Search) in determining the most optimal ensemble weight contribution configuration, thereby serving as a benchmark for selecting optimization methods in similar cases.

4. Yielding scientific recommendations regarding the ideal and optimal dataset splitting strategy for training architectural models on medical datasets, in order to maintain a balance between generalization capabilities and the prevention of overfitting phenomena.
5. Assisting medical personnel in performing classifications and providing provisional diagnoses for Tinea Capitis disease more rapidly, precisely, and accurately, as well as reducing the risk of diagnostic errors resulting from interpretative subjectivity among medical personnel and the visual similarities of medical images across disease subtypes.
6. Serving as an alternative solution for healthcare facilities with limited modern diagnostic tools and equipment, considering that the architectural model based on deep learning and ensemble learning is capable of being implemented using standard digital images.

1.5. Scope and Limitations

To maintain the focus, targets, and objectives of the research as previously elaborated, several problem limitations have been established. The scope and the limitations of this research include the following:

1. The Tinea Capitis skin disease image dataset is sourced from RSUD Haji Provinsi Jawa Timur and public repositories on the internet.
2. The classification is performed on 6 (six) categorical classes, namely the Kerion, Favus, Diffuse Pustular, Black Dot, Gray Patch, and Healthy Skin.
3. The data augmentation techniques encompass geometric rotation, image flipping, and brightness adjustment to balance the class distribution.
4. The testing employs 3 (three) dataset splitting scenarios, namely Scenario 1 (70:20:10), Scenario 2 (80:15:5), and Scenario 3 (60:25:15).
5. The deep learning models utilized are restricted to the ResNet-50 and the EfficientNet-B2 architecture, acting as the base learners and single models.
6. The ensemble learning method employed in this research is strictly limited to the Soft Voting Ensemble Learning approach.
7. The performance evaluation is conducted utilizing evaluation metrics such as accuracy, precision, recall, F1-score, specificity, and false positive rate.