CHAPTER I
INTRODUCTION

1.1. Background

According to the latest report from the World Stroke Organization for 2025, stroke remains the second leading cause of death and disability worldwide, with more than 93.8 million people suffering from stroke and approximately 7 million people dying each year. More than 80% of stroke cases can actually be prevented by managing risk factors such as hypertension, smoking, obesity, diabetes, and an unhealthy lifestyle. However, significant disparities in access to prevention, diagnosis, and rehabilitation services mean that low- and middle-income countries bear up to 89% of the global stroke burden. This situation underscores that stroke is not merely a medical issue but also a social and economic crisis requiring global strategies based on prevention, equitable access to healthcare, and increased public awareness [1].

In Indonesia itself, compared to other countries in Southeast Asia, Indonesia ranks highest in terms of age- and sex-adjusted mortality rates, at 193.3 per 100,000 population, as well as in terms of Disability-Adjusted Life Years (DALYs) lost, at 3,382.2 per 100,000. Based on national data, the prevalence of stroke in rural areas is 0.0017%, while in urban areas it is 0.022%, with significant regional variations, the lowest in Papua and the highest in West Kalimantan. The RISKESDAS report also indicates an overall prevalence of 10.9 per 1,000,000 population, signaling an increase in the burden of this disease across various provinces [2].

By type, strokes are divided into ischemic strokes, which account for 60% to 70% of global cases, and intracerebral hemorrhage (ICH), or hemorrhagic stroke, which is far more common in developing countries. The fundamental difference lies in the presence of infarction in brain tissue. Acute Ischemic Stroke (AIS) is characterized by sudden neurological dysfunction accompanied by evidence of infarction on imaging, while a Transient Ischemic Attack (TIA) is a temporary episode without evidence of permanent infarction. Early detection is crucial because patients who experience a TIA have a 7.5% to 17.4% risk of recurrent stroke within the following three months if not treated promptly [3].

This situation highlights the need for machine learning-based predictive analysis, a systematic process for studying patterns in historical patient data to inform

clinical decision-making with the aim of assisting healthcare professionals without the need for explicitly programmed rules. This predictive analysis involves feature extraction from clinical attributes such as age, history of hypertension, history of heart disease, blood sugar levels, gender, marital status, occupation, type of residence, BMI, and smoking status to objectively model the probability of stroke occurrence in an individual [4].

In this study, model performance was measured using numerical evaluation metrics such as accuracy and recall to improve the efficiency of medical diagnosis and the accuracy of predictions [5]. However, a major issue arises in that high-accuracy machine learning algorithms such as Random Forest, XGboost, and Artificial Neural Networks are often "black-box" in nature, making their predictions difficult for healthcare professionals to understand [6]. In a medical context, interpretability is a crucial aspect because clinical decisions involve human lives and must be rationally explained and justified. Models that prioritize accuracy over transparency carry the potential risk of medical errors because users do not understand the contribution of each risk factor to the prediction results [7].

To address these challenges, this study proposes a solution using the Stacking Classifier approach. This ensemble learning technique operates on a hierarchical principle that combines several algorithms across two learning levels. At the first level (base learners), several algorithms with distinct learning characteristics are used: Logistic Regression, Random Forest, and Xgboost. Subsequently, the prediction results from this first level do not immediately become the final result but are instead used as new input for the second level, namely a meta-learner based on an Artificial Neural Network (ANN) [8].

An Artificial Neural Network (ANN) is a computational model designed based on the structure and function of the human biological nervous system, consisting of an input layer, hidden layers, and an output layer. This technology has the adaptive ability to learn independently from given data and identify patterns or trends that are too complex to be detected by humans or conventional computer systems. Thanks to its superiority in processing non-linear data, ANN has been widely applied in various strategic fields, ranging from facial and handwriting recognition, natural language processing (NLP), to enhancing data security through intrusion detection systems and the identification of phishing and spam in emails [9].

The role of the ANN meta-learner in a model stacking approach is to intelligently learn how to combine the predictions of the base learners, minimize bias, and correct error patterns from the base models [9]. Through this combination mechanism, model stacking is able to produce more stable predictions with higher accuracy compared to using individual models independently [4].

To ensure the resulting model is not a "black box," the Explainable Artificial Intelligence (XAI) method was developed to create AI systems with high transparency that can provide concise and easy-to-understand explanations regarding the reasoning behind a prediction. The presence of XAI is crucial in the healthcare sector to build healthcare professionals' trust in digital technology, while ensuring that clinical decisions made are medically accountable. XAI is crucial in the healthcare sector to build healthcare professionals' trust in digital technology, while ensuring that clinical decisions made are medically justifiable [7].

In its implementation, this study uses two main interpretation techniques or frameworks: LIME (Local Interpretable Model-agnostic Explanations) and SHAP (SHapley Additive Explanations). LIME operates on a local scale by training a simple surrogate model around a specific data point to demonstrate the contribution of specific features to an individual patient's predicted outcome. Meanwhile, SHAP uses a coalition game theory-based approach to calculate the Shapley value of each feature, enabling the identification of the average impact of each variable on the model as a whole (global interpretation) as well as at the individual case level. With this XAI interpretation, the model not only presents stroke risk probabilities but also provides in-depth insights into the dominant risk factors underlying a patient's health condition, thereby supporting more proactive and personalized medical interventions [10].

1.2. Problem Formulation

The research problems in this study are:

1. How can a Stacking Classifier model be built and optimized using base learners (LR, RF, XGboost) with an ANN meta-learner to predict stroke?
2. How does the performance of the Stacking Classifier model compare to that of individual models in detecting stroke risk based on evaluation metrics derived from the confusion matrix, such as accuracy, precision, recall, F1-score, and ROC score?

3. How can Explainable Artificial Intelligence (XAI) methods, specifically the SHAP and LIME approaches be applied to provide transparency in the Stacking Classifier's prediction results through global and local interpretations, as well as to identify the most significant clinical features related to stroke risk and the contributions of the base learners to the ANN meta-learner's final decision?
4. How can the developed Stacking Classifier model be implemented into a web-based graphical user interface (GUI) to support interactive and transparent visualization of prediction results and XAI interpretations?

1.3. Research Objectives

The objectives of this research study are to:

1. Develop and optimize a stroke prediction model using the Stacking Classifier approach, which combines Logistic Regression, Random Forest, and XGboost algorithms as base learners with an Artificial Neural Network (ANN) as the meta-learner.
2. Evaluate and compare the performance of the Stacking Classifier model against individual models in predicting stroke risk based on evaluation metrics derived from the confusion matrix, such as accuracy, precision, recall, F1-score, and ROC score.
3. Apply Explainable Artificial Intelligence (XAI) methods using the SHAP and LIME approaches to provide transparency in the Stacking Classifier model through global and local interpretations, in order to identify the most significant clinical features and analyze the relative contribution of each base model to the final decision of the ANN meta-learner.
4. Implement the Stacking Classifier model and XAI visualizations into a web-based graphical user interface (GUI) as an interactive, transparent, and easy-to-understand self-service early detection tool for the general public..

1.4. Research Limitations

The limitations of this research study is as follows:

1. This study uses only clinical tabular data consisting of attributes such as age, gender, blood pressure, history of hypertension, history of heart

disease, glucose levels, BMI, smoking status, occupation, and type of residence.

2. The dataset used in this study is a combination of 5,110 secondary data points from the open-source Kaggle website and primary data from community health centers.
3. The predictive models used are limited to three basic algorithms: Logistic Regression, Random Forest, and XGboost, which are then combined using a Stacking Classifier with an ANN meta-learner.
4. Explainable Artificial Intelligence (XAI) was limited to two methods: SHAP for global interpretation and LIME for local interpretation.
5. The research results were implemented in the form of a web-based graphical user interface (GUI) that serves as a tool for visualizing prediction results and model interpretations; however, it is not intended to replace the final medical diagnosis made by healthcare professionals.

1.5. Research Benefits

This study is expected to provide the following benefits:

1. Contribute to the scientific literature in the fields of machine learning and Explainable AI (XAI) and serve as an academic reference for future research.
2. To provide an accurate and transparent stroke prediction model to assist healthcare professionals in clinical decision-making.
3. The research findings are expected to help the public and healthcare institutions prioritize stroke prevention strategies more effectively.