

CHAPTER I

INTRODUCTION

1.1 Project Background

Furniture factories and sawmills are major contributors to wood waste generated by the wood processing industry in Indonesia. National reports state that annual wood waste production is in the range of 12–16 million m³ with an upward trend of around 10–15% compared to 2014, and most of this waste is stored in warehouses for further processing or recycling. Dry wood waste is highly flammable, so small ignition sources such as friction, static electricity, or hidden heat sources can quickly trigger fires in storage areas.

The statistics of disaster incidents in Indonesia shows that on average there are 550-750 and 25-35 fire incidents at the warehouses in 2022-2024 respectively with the differing percentage involving the use of inflammable materials, including wood. Examples of environmental effects caused by wood storage facilities include smoke, ash (pollution), and carbon releases, failure to detect and put out fires in time can lead to the destruction of assets, health hazards to the workers, and other impacts as have already been experienced in a series of several recent cases in Jakarta and Surabaya (Department of Mechanical and Manufacturing Engineering, Faculty of Engineering and Built Environment, Universiti Kebangsaan Malaysia, 43600 UKM Bangi, Malaysia et al., 2025).

Conventional fire detection technologies, such as smoke and thermal sensors, tend to be reactive and only respond once smoke or high heat is present, which is often too late for large, sparsely monitored warehouse environments. According to recent research, it is possible to equip Internet of Things (IoT) sensors with AI models like Long Short Term Memory (LSTM) and identify a fire earlier and more accurately by learning the temporal adaptation of temperature, humidity, and gas

measurements. LSTM and hybrid CNNLSTM studies in IoT based fire detection systems have reported accuracy of above 90 percent and increased capabilities to provide early warnings as opposed to threshold-based or traditional systems (Ahmad Nawawi et al., 2025).

The project above concentrates on the making of a prototype of LSTM that is based on AI as a fire detector within wood warehouses. The sensor data (temperature, humidity, and gas) is fed through the system and an inference of the degree of risk of fire is made and early notification is provided. This is done by forcing users to physically unlock an application, which is typical of current IoT fire monitoring prototypes. The proposed project will shorten the time of detection and attempt to prevent losses in the environment and economy of wood waste storage facilities by integrating predictive analytics of LSTM and automated web push notifications (M Wahidin et al., 2021).

1.2 Problem Statement

Wood waste warehouses have fire detection systems that are mostly either based on conventional threshold-based or rule-based approaches and cannot detect the dynamic trends and subtle early warning signs of fire like slow temperature changes or humidity changes. These constraints prevent the active prediction of hazards because fixed limits are not able to change according to the dynamism of environmental sequences which are characteristic of wood waste storage. This gap has been worsened by the lack of AI-based Long Short-Term Memory (LSTM) models, making it impossible to analyze both past and real-time sources to identify early on the appropriate information.

Stockpile of dry wood debris in storage warehouses goes a long way towards enhancing the risk of fire due to the high combustibility of this material and its ease of ignition in presence of sparks or localized sources of heat. The piled stacking slows down the air flow, and under such

conditions, hot spots and smoldering combustion are formed, hard to identify at the initial stages. Human supervision (especially at night shifts or when there is no working process) also makes it more difficult to detect any initial evidence of overheating or smoldering, and this issue is a constant in the case studies of using IoT-based fire detection in industrial and building settings (Simanungkalit & Rambe, 2025).

The fact that the real-time alarm systems in wood waste warehouses are not in place worsens the fire risks as sparks and other sources of ignition usually pass unnoticed because of poor human watch especially when the warehouses are not in operation. Such low flow of information translates to delayed response, which increases the number of casualties and damage since workers and emergency responders fail to receive important initial information on fire outbreaks. In the absence of timely alerts, the chances of severe escalation grow and costly in economic terms, health risks and pollution of the environment by smoke and ash have become a reality, as seen in the recurrent incidences in Indonesia where early intervention would have helped alleviate extreme effects.

1.3 Project Objectives

In this project, wood waste warehouse early detection device is being developed and piloted with the help of an AI-based LSTM model.

In particular, the objectives of the project include:

- i. To Implement an AI-based Long Short-Term Memory (LSTM) model for early fire detection in wood waste warehouse environments.
- ii. To create and engineer an LSTM model to forecast fire hazards using real time sensor measurements, and target sensitivity.
- iii. To integrate a rapid automatic alert mechanism into the prototype system so that detection and notification times.

1.4 Project Scope

1.4.1 Scope of System

The scope of the system will include the design of a prototype of the IoT sensors, which combines an artificial intelligence-based Long Short-Term Memory (LSTM) model with the creation of an early fire warning system in wood waste warehouses. This is a response to shortcomings of traditional threshold based approaches as it allows one to examine time trends in environmental data. Hardware devices involve DHT22 temperature/humidity sensors, MQ-135 CO/ CO₂ sensors, and IoTs, like Raspberry Pi to obtain measurements.

Information is gathered sequentially or within brief periods to feed the LSTM with information. The LSTM model is used to examine the sequence of sensor data to determine patterns of fire risk that cannot be detected by fixed values. Condition processing results present conditions as normal, warning, or danger, and create automated alerts using Web Push services using RESTful API (Sasmoko & Mahendra, 2017)

The prototype does not include any other features other than LSTM integration, including cloud storage, interactive dashboards, or manual controls. This is tested on the performance of LSTM, sensor reliability, and delivery of alerts on simulated warehouse environments. Architecture and model specifications, source code, and performance reports are documented in accordance with project objectives (Alkautsar et al., 2021).

1.4.2 Scope of User

The user scope focuses on the warehouse employees and security guards who get a LSTM-generated notification about early fire response and do not have any system management duties. Notifications

are sent using Web Push to Web Browsers or mobile apps, and they indicate risk levels based on LSTM time analyses, real-time sensor indicators of trends of the environment, and likely short-term actions, including inspection or evacuation planning in the area. According to this design, situational awareness is achieved quickly especially at night shifts or weekends where human oversight is minimal and traditional detection systems usually do not detect smoldering patterns in time.

The LSTM-classified risk evaluations and simple historical sensor trends are updated and made available to the users in limited read-only API endpoints that are used particularly to engage passive monitoring applications. This functionality permits the rapid verification of the current conditions without authorizing any data editing, threshold adjustments, system setups as well as operational interventions that might jeopardize the entirely automated process of detection. The core advantages are directly related to reported fire dangers due to wood waste piles, piling of dense materials that block the airflow, and forming undetected hot spots based on the high level of temporal pattern recognition associated with LSTM over traditional methods (Park et al., 2023).

Simulated fire scenarios prove the speed of notification delivery, message readability during stressful situations, understanding of the user of LSTM-based risk indicators, and the effectiveness in general in anticipating the relevant protective response. The fully automated system design does not need user authentication, or login process, did not need to modify parameters, or to have any interactive functionality, being smoothly functional and directly serving the project aim of automated integration of early warning and keeping the focus on prototype-scale implementation (Handoko & Priyadi, 2025).

1.4.3 Scope of Admin

The developer, data scientist and test technician areas involve administering the full LSTM prototype life cycle under controlled laboratory environments that replicate the wood waste warehouse environment. Initial settings are done directly via IoT hardware interfaces such as accurate sensor calibration protocols, LSTM hyperparameter optimization such as sequence window length, LSTM layers, learning rate fine-tuning, and batch size parameters and full API connectivity verification without using external web interfaces and third-party platforms.

Historical real time data measurements of the performance of LSTM models such as prediction confidence scores, sequential data pattern recognition accuracy, sensor input integrity validation, successful transmission of alerts and overall system health metrics are logged via detailed local logging systems. Such close monitoring allows quick detection and correction of errors like drift in model behavior due to alterations in environmental baselines, sensor data quality degradation, or communication latency that may compromise the early detection of fires which is the source of critical constraints in traditional threshold-based systems as described in the problem statement (Maulana, 2025).

The protocols of risk mitigation include regular verification of sensor reliability via regular calibration tests, the presence of strong network failure risks in the event of intermittent connectivity, retraining of LSTM models with the help of the test information, and having a full fallback pathway to maintain uninterrupted early warning features. Any development, testing, and validation is limited to operations of prototype scale, with technical documentation focused on the specifications of LSTM architecture, training/validation datasets based on warehouse simulation, full source code

repositories, performance benchmarking results, and comprehensive implementation procedures that offer full traceability to the underlying project goals of LSTM model implementation, environmental factor analysis, and automated integration of a notification system (Manurung et al., n.d.).

1.5 Project Significance

The project is focused on the essential issues of industrial safety and waste management since it aims at identifying the threat of fire earlier in wood waste warehouses. With the implementation of an AI-based LSTM system that detects fire along with IoT sensors and web push notifications, the risk of catastrophic fire can be minimized significantly, which will result in fewer economic costs in terms of damage to assets, downtime, and fire fighting. Experiments with early fire detection in industrial and forest settings have shown that predictive systems based on LSTM and similar models can significantly minimize losses in contrast to purely reactive mechanisms of detecting fires.

In addition to the benefits associated with the economy, the project promotes the sustainability of the environment by avoiding the mass burning of the wood waste that would otherwise lead to air pollution and the emission of greenhouse gases. Safety-wise, the quicker detection and notification enhances security of workers and surrounding communities, which is one of the objectives of an array of IoT-driven fire safety and smart homes applications. In the academic sphere, this project has demonstrated a practical implementation of AI and deep learning (LSTM) in the resolution of real safety issues in the world, and can be used as a reference in further studies of AI-based risk detection and intelligent industrial monitoring systems.

1.6 Chapter Summary

The chapter has introduced the background and motivation to develop an AI based LSTM based early fire detection system in wood waste warehouses with the support of the national statistics on wood waste generation and fire outbreak in wood warehouses. It also emphasized the flammability of dry wood, the prevalence of warehouse fires and the inefficiency of the traditional fire detecting technology to deliver effective alerts to large storage facilities.

The primary issues which can be singled out include the fire hazards which are presented by the stored wood waste and the absence of real-time predictive alarms. To solve these problems, this project suggests developing a prototype, which will combine IoT sensors, an LSTM-based predictive model, and a web-based notification system to enhance early detection and response time. The chapter also introduced the objectives of the project, the scope of the system, and the contributions that are to be made, and the following chapter discusses the literature on the use of IoT-based fire detection systems, LSTM methods, evaluation metrics, and the current solutions.