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Visual Detection of Fouling in Wood-Fired Boilers Using a Lightweight Convolutional Neural Network for Energy Efficiency in Small-Scale Industries

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Abstract. *The tempeh industry, as part of the Micro, Small, and Medium Enterprises (MSME) sector, plays a vital role but often faces challenges in energy efficiency, particularly in wood-fired boilers. A significant decline in boiler efficiency is caused by the accumulation of soot and ash (fouling), which hinders heat transfer. Boiler cleaning practices that are still manual and based on fixed schedules lead to fuel wastage and inconsistencies in the production process. This study proposes an innovative and cost-effective fouling monitoring system using a Convolutional Neural Network (CNN) with a MobileNetV2 architecture. The system utilizes an endoscope camera installed in the Flue Gas Chamber to capture images of the internal condition of the boiler. This area is strategically selected because it functionally represents the cumulative condition of the fire tubes while providing more practical and holistic visual access. The trained CNN model analyzes these images to objectively classify the level of fouling, enabling a shift from reactive maintenance strategies to predictive, condition-based maintenance. Implementation results in an MSME tempeh production facility show significant impacts: a 10% reduction in wood fuel consumption and up to a 50% decrease in manual cleaning frequency. Economically, this translates to an annual operational cost saving of IDR 6,300,000 and a return on investment (ROI) period of less than one year. This study demonstrates that the application of AI-based computer vision is an effective, feasible, and impactful solution to enhance the competitiveness and sustainability of MSMEs.*

Keywords *Industrial Boiler, MobileNetV2, Energy Efficiency, Fouling, Flue Gas Chamber, Tempeh Industry, Predictive Maintenance, MSMEs.*

INTRODUCTION

Fouling is the primary enemy of boiler efficiency (Bujak et al., 2020). In wood-fired boilers, flames and hot gases from combustion contain fine unburned solid particles (soot and ash). These gases flow through the inner parts of fire tubes submerged in water to transfer heat. Over time, these particles adhere, accumulate, and form thick deposits on the inner walls of the tubes. This deposit layer acts as a highly effective thermal insulator, hindering heat transfer from flue gas to water (Green & Perry, 2018). As a result, the boiler must work harder (consume more wood fuel) to achieve the desired steam temperature and pressure. To understand the working mechanism and the location of the problem, a schematic of a commonly used vertical fire-tube boiler is shown in Figure 1.

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Figure 1. Working Scheme of a Vertical Wood-Fired Boiler

Figure 1 shows that flames and hot gases from combustion (combustion chamber) pass through the fire tubes submerged in water. The main problem does not only occur inside the tubes but also accumulates significantly in the flue gas chamber, where exhaust gases from all tubes are collected before being discharged through the chimney. In this area, gas velocity decreases, causing soot and ash to settle and cover the tube ends and chamber walls. This accumulation not only reduces the residual heat that can be absorbed but can also block gas flow, making combustion in the furnace inefficient.

Currently, MSMEs generally rely on two suboptimal cleaning methods: (1) schedule-based cleaning, such as once a month, which risks cleaning too early or too late when fouling has already become severe; and (2) operator subjective judgment, which relies on experience and indirect indicators such as prolonged boiling time. Both methods are reactive and inefficient, resulting in significant resource waste over weeks before action is taken.

Research Objectives

Based on the identified problems, this study aims to:

1. Develop a computer vision–based fouling monitoring system using a Convolutional Neural Network (CNN) with a MobileNetV2 architecture that can automatically and objectively classify fouling levels in the flue gas chamber.
2. Analyze the effectiveness and accuracy of the developed CNN model in detecting fouling levels compared to subjective operator assessments.
3. Measure and quantify the impact of CNN system implementation on boiler operational efficiency, including fuel consumption, cleaning frequency, and production stability.

Research Contributions

This study is expected to provide meaningful contributions from multiple perspectives. From a practical standpoint, the results offer a technological solution that can be directly adopted by MSMEs. By providing an affordable system with a fast return on investment (ROI), this study offers strong economic incentives for MSMEs to transition from conventional maintenance practices to data-driven systems. This transition not only reduces operational costs through optimized fuel usage but also improves product quality consistency and reduces manual workload.

From a theoretical perspective, this study contributes to the development of literature in artificial intelligence and energy management by presenting a concrete case study on the application of "frugal AI," namely innovative yet cost-efficient AI implementation in traditional and small-scale industrial sectors that are often overlooked. Ultimately, these benefits extend to broader social and economic impacts, where improved efficiency and productivity of MSMEs contribute directly to increased competitiveness and promote the adoption of more sustainable and responsible production practices.

Scope of the Study

To maintain focus and ensure depth of analysis, this study limits its scope to a specific context. The research subject is a single vertical fire-tube wood-fired boiler with a capacity of 300 kg/hour operating in an MSME tempeh production facility. The visual monitoring system focuses exclusively on the flue gas chamber, which serves as a cumulative indicator of fouling conditions throughout the fire-tube system.

From a technical perspective, the Convolutional Neural Network used in this study is the MobileNetV2 architecture, with functionality limited to fouling level classification. It is important to note that this study does not develop an automated cleaning system. Instead, it focuses on creating a decision support system that provides accurate and timely recommendations for manual cleaning actions by the operator. Therefore, the scope of this study is limited to diagnostic and predictive aspects rather than automation.

LITERATURE REVIEW

Energy Efficiency in Small-Scale Industries: A Review of Fouling Phenomena and AI-Based Monitoring Solutions

A comprehensive review of relevant literature builds the theoretical framework and context for this study. The discussion begins with a macro perspective on the urgency of energy efficiency in Micro, Small, and Medium Enterprises (MSMEs), then narrows down to the technical specifications of solid-fuel boilers. The focus then shifts to the fouling phenomenon as the core problem and the evolution of maintenance strategies, and concludes with the exploration of Convolutional Neural Networks (CNN) as an innovative solution. This discussion aims to clarify the position of this study within the current body of knowledge while identifying research gaps that form the basis of its originality and contribution.

Energy Efficiency Challenges in the MSME Sector

The Micro, Small, and Medium Enterprises (MSME) sector is the backbone of the global economy, especially in developing countries, contributing significantly to GDP and employment. However, despite its economic contribution, this sector often faces challenges in productivity and competitiveness, one of which is low energy efficiency (Trianni et al., 2013). Many MSMEs, particularly in the food and beverage processing industry, still rely on conventional and inefficient process technologies. Energy waste not only directly increases operational costs but also impacts carbon emissions and environmental sustainability. Therefore, improving energy efficiency in the MSME sector is no longer merely an option but an economic and environmental imperative. Previous studies have largely focused on energy audits and policy interventions; however, affordable and easily adoptable technological solutions at the shop-floor level remain limited.

Solid-Fuel Boilers in Food Processing Industries

In many food-processing MSMEs, such as tempeh, tofu, and drying industries, solid-fuel boilers (wood, palm shells, or coal) serve as the primary heat source due to their abundant availability and relatively low cost. The commonly used boiler type is the fire-tube boiler, in which flames and hot gases from combustion flow through tubes submerged in water. Although the construction is simple and robust, the thermal efficiency of this type of boiler is highly susceptible to degradation due to long-term operation. Boiling and sterilization processes in the food industry require a stable and consistent steam supply, making boiler performance a critical factor in determining the quality and safety of the final product (Sudarmadji et al., 1997). Therefore, maintaining boiler efficiency is not only a matter of fuel savings but also of ensuring production quality.

Fouling Phenomenon in Solid-Fuel Boilers

The core cause of efficiency degradation in solid-fuel boilers is the fouling phenomenon. Fouling is defined as the accumulation of unwanted materials on heat transfer surfaces. In wood-fired boilers, these materials mainly consist of soot (fine carbon particles from incomplete combustion) and ash (mineral residues). These deposits adhere to the inner walls of fire tubes and, cumulatively, to the flue gas chamber. According to Buecker (2012), fouling layers have very low thermal conductivity, far below that of the pipe metal itself. This makes them act as insulating layers that significantly hinder heat transfer from flue gas to water. As a result, achieving the same steam production rate requires higher flue gas temperatures, which means increased fuel consumption. Studies have shown that even a 1 mm soot layer can increase fuel consumption by 2–3%, a value that becomes highly significant over long-term operation.

Evolution of Maintenance Strategies: From Reactive to Predictive

To mitigate the negative impact of fouling, various maintenance strategies have been developed. The most traditional approach is reactive maintenance, where repair or cleaning actions are only taken after significant damage or performance degradation occurs. This approach is the least efficient and carries a high risk of permanent equipment damage.

A more advanced approach is time-based preventive maintenance, where cleaning is scheduled periodically (e.g., monthly). Although better than reactive maintenance, this strategy is often suboptimal because it does not consider the actual condition of the boiler, potentially leading to premature cleaning (wasting resources) or delayed cleaning (causing prolonged energy waste).

The latest paradigm in industrial practice is predictive maintenance, where maintenance actions are scheduled based on real-time equipment conditions monitored using sensors and data analysis (Vogl et al., 2019). However, the implementation of predictive maintenance in MSMEs remains very limited due to high sensor costs and system complexity.

Convolutional Neural Networks for Industrial Visual Inspection

In the past decade, Convolutional Neural Networks (CNNs) have revolutionized the field of computer vision and become powerful tools for classification and object detection tasks. CNNs automatically learn hierarchical features from images, ranging from simple edges and textures to complex objects, without the need for manual feature engineering (Krizhevsky et al., 2012).

This capability has been successfully applied to various industrial inspection tasks, such as detecting cracks on metal surfaces, identifying defects in manufactured products, and monitoring equipment conditions. Modern CNN architectures such as MobileNetV2 are specifically designed for edge computing applications with limited resources, offering an optimal balance between high accuracy and computational efficiency (Sandler et al., 2018). This opens opportunities for implementing cost-effective and practical AI-based vision systems in various environments, including MSME sectors.

Research Gap and Contribution

Based on the literature review, a significant research gap is identified. While CNNs have proven effective for visual inspection in large-scale industries and fouling has long been recognized as a critical issue in boiler performance, the application of CNNs for visual fouling monitoring in MSME-scale boilers remains very limited. Most studies on boiler predictive maintenance focus on analyzing sensor data such as temperature, pressure, and flow, which require numerous sensors and complex control systems.

Cost-effective and easy-to-implement computer vision–based approaches have not been extensively explored. Therefore, this study contributes to filling this gap by proposing and implementing a CNN-based fouling monitoring system using the MobileNetV2 architecture, focusing on visual images from the flue gas chamber. This study uniquely combines the principles of frugal AI with the practical needs of MSMEs, offering a solution that is not only technically reliable but also economically feasible and directly impactful.

METHODS

This study uses an experimental approach to evaluate the impact of an AI-based solution on boiler efficiency. The methodology is systematically designed to ensure the validity, reliability, and reproducibility of the findings. The following sections describe the research design, subject and location, variable identification, proposed system architecture, data collection procedures, and data analysis techniques used to evaluate the effectiveness of the solution.

Research Design

To isolate and measure the effect of implementing the CNN-based monitoring system, this study adopts a one-group pre-test–post-test experimental design. This design is appropriate for evaluating the impact of a specific intervention on the same subject by comparing conditions before and after implementation. This approach allows control over confounding variables, as the subject characteristics (in this case, the boiler unit) remain constant. Formally, the design can be represented as O_1 X O_2, where O_1 is the baseline measurement (pre-test), X is the treatment (implementation of the CNN system), and O_2 is the post-treatment measurement (post-test). Statistical comparison between O_1 and O_2 forms the basis for determining the significance of the treatment effect.

Subject and Research Location

This study was conducted at a Micro, Small, and Medium Enterprise (MSME) tempeh producer in Bogor, West Java, "Tempe Makmur." The location was selected due to its representativeness of MSME food industries that still utilize conventional boiler technology. The research subject is a vertical fire-tube wood-fired boiler, which serves as the core of the steam production process. The technical specifications are as follows: steam capacity of 300 kg/hour, maximum operating pressure of 8 bar, and wood fuel as the primary energy source. The boiler has been in operation for approximately five years and includes an inspection port in the combustion chamber wall, allowing the installation of an image acquisition system without significant structural modification, making it an ideal platform for this experiment.

Research Variables

Variables are clearly defined to ensure validity. The independent variable is the implementation of the CNN-based fouling monitoring system, which serves as the treatment. The impact of this treatment is measured through several dependent variables: (1) daily fuel consumption (kg/day), (2) boiler cleaning frequency (times/month), (3) time required to reach operating pressure (minutes), and (4) steam pressure stability during operation. Meanwhile, to ensure that observed changes in dependent variables are truly caused by the independent variable, several control variables are maintained constant throughout the study, including boiler type and specifications, type and moisture content of the wood fuel, daily production load (amount of soybeans processed), and boiler feedwater source.

System Architecture and Data Acquisition

The developed system is designed with a philosophy of minimal invasiveness, cost efficiency, and autonomy. The overall architecture consists of three integrated main components: image acquisition hardware, edge processing unit, and user interface. Each component is carefully selected and designed to address the unique challenges of a wood-fired boiler environment, which is highly dusty, hot, and subject to vibration.

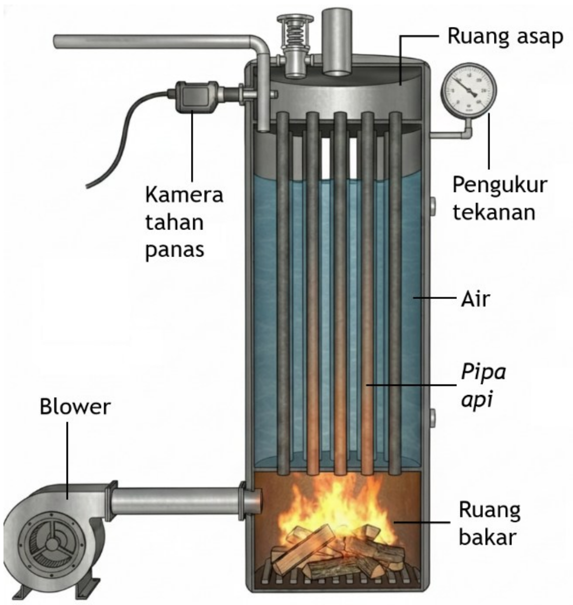

Figure 2. Installation Modeling of a Heat-Resistant Camera in the Flue Gas Chamber

The first component is the image acquisition hardware. Since the flue gas chamber is the most representative cumulative indicator, the camera is strategically installed in this area, as illustrated in Figure 2. The hardware utilizes a high-temperature industrial camera (FLIR A315) with a resolution of 320×240 pixels, a temperature range of 20°C to 650°C, and a stainless-steel housing. The camera faces the chamber through an inspection port equipped with a heat-resistant quartz glass window. Its fixed orientation targets the junction between the ends of the fire tubes and the chamber ceiling, which is the area most prone to soot accumulation. To keep the lens clean from ash, a low-pressure air purge system operates shortly before image capture.

The second component is the edge processing unit and CNN model. A mini-computer, Raspberry Pi 4 Model B with 4GB RAM, functions as the local processing unit. It controls the camera, performs image preprocessing, runs model inference, and stores results. The selection of the CNN architecture is a crucial step. This study applies the MobileNetV2 architecture developed by Google, where Figure 3 illustrates the processing flow from flue gas image input to classification output.

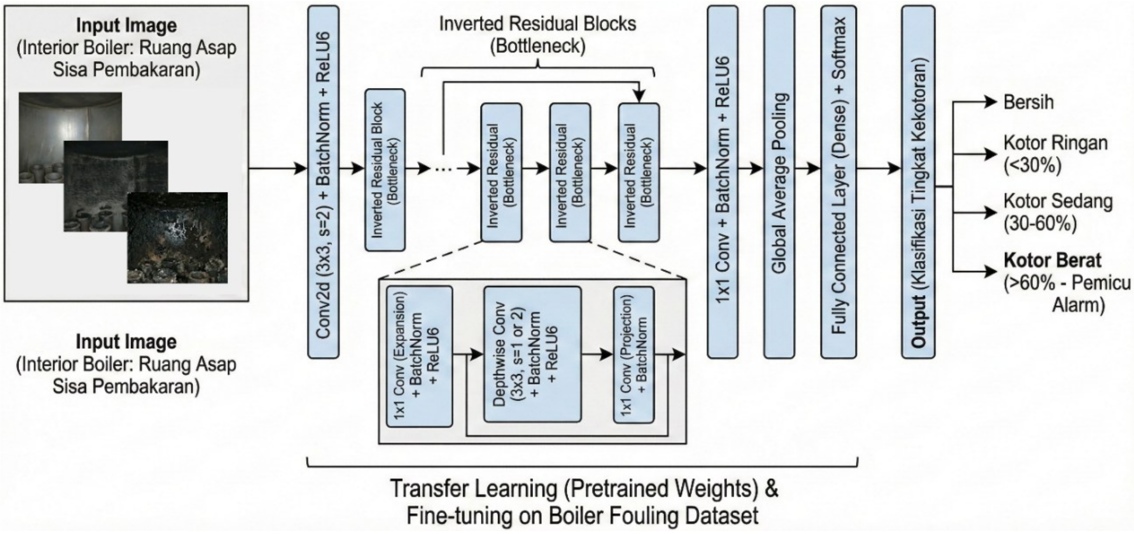

Figure 3. MobileNetV2 Model Architecture for Fouling Image Classification

The choice of MobileNetV2 is based on computational efficiency considerations. This architecture uses depthwise separable convolutions, significantly reducing the number of parameters and computational load compared to standard CNNs without sacrificing accuracy. This makes MobileNetV2 ideal for deployment on edge devices such as Raspberry Pi, enabling real-time and offline operation.

Figure 3 illustrates the complete data processing pipeline of the proposed fouling detection system, from raw image acquisition to classification decision, implemented on an edge device (Raspberry Pi), as follows:

1. **Image Input (Data Acquisition)**
   The pipeline begins with RGB digital images captured from the interior of the flue gas chamber. These images show varying conditions of the fire tubes, ranging from clean (visible metal surface) to heavily covered with soot. The system processes these images as input for further analysis.
2. **Feature Extraction (Backbone)**

The core of the model lies in the inverted residual blocks (bottleneck structure). This structure utilizes depthwise separable convolutions, separating spatial and depth processing, thereby significantly reducing computational cost and model parameters while maintaining high accuracy.

3. **Classification and Output**

   Extracted features are processed through a Global Average Pooling layer and a Fully Connected (Dense) layer. A Softmax activation function converts the output into probability values across four fouling classes:

   - Clean
   - Light Fouling (<30%)
   - Moderate Fouling (30–60%)
   - Heavy Fouling (>60%)

4. **Decision Logic (Decision Support System)**

   The system highlights the "Heavy Fouling" class as a trigger for alarms. Notifications are only sent when critical fouling (>60%) is detected, indicating the need for immediate cleaning action.

5. **Training Strategy**

   The model is not trained from scratch but uses transfer learning with pretrained weights, followed by fine-tuning using a dataset of boiler fouling images (300 images). This approach accelerates convergence and improves accuracy despite limited data.

The notification logic is conservative, where cleaning recommendations are issued only if the CNN consistently classifies the condition as "Heavy Fouling" in two consecutive image captures. A locally hosted web-based dashboard enables operator interaction, displaying the latest images, classification results, and historical fouling trends to provide full transparency of boiler conditions.

Research Procedure and Dataset Formation

The research procedure was carried out in three sequential stages to ensure systematic and valid data collection. The first stage was baseline data collection (pre-test), conducted over 30 days before the CNN system was installed. During this stage, operators were asked to record daily operational data in a logbook. This stage was also used to build the initial dataset. Each day, one image was manually captured through the inspection port. The image labeling process was conducted collaboratively by an experienced operator and a researcher to reach a consensus. Consistency and objectivity in labeling were achieved by following a structured visual guideline. Table 2 summarizes the criteria of this guideline, while Figure 4 presents visual examples of each class in the dataset.

Table 2. Visual Labeling Criteria for Fouling Levels in the Flue Gas Chamber

Classification Class	Visual Criteria
Clean	The surfaces of the tube ends and the chamber ceiling are clearly visible, with no or only a very thin layer of soot deposits.
Light Fouling (<30%)	Soot appears as a thin layer covering a small portion of the surface, but the metal structure is still predominantly visible.
Moderate Fouling (30–60%)	Soot covers most of the surface, forming a clearly visible layer, but gaps or thinner areas are still present.
Heavy Fouling (>60%)	The surface is almost entirely covered by a thick and dense soot layer, sometimes forming slag deposits.

Figure 4. Visual Examples of Flue Gas Chamber Conditions Dataset (Figure 4a: Clean | Figure 4b: Light Fouling | Figure 4c: Moderate Fouling | Figure 4d: Heavy Fouling)

From this 30-day process, a total of 300 labeled images were collected. The second stage was the development and training of the CNN model. The dataset of 300 images was divided into 80% for the training set, 10% for the validation set, and 10% for the testing set. The MobileNetV2 model was trained using the Adam optimizer with a learning rate of 0.0001 for 50 epochs and a batch size of 16.

The third stage was system implementation and post-test data collection, where the developed system was installed and operational data were recorded for the following 30 days, with cleaning decisions based on system notifications.

Data Analysis Technique

The collected data were analyzed comprehensively to address each research objective. Model performance was evaluated using accuracy, precision, recall, F1-score, and a confusion matrix. Operational impact analysis was conducted by statistically comparing pre-test and post-test data using a Paired Samples T-Test. This study uses standardized formulas to quantify economic impact. Fuel consumption savings are calculated as:

$$\text{Fuel Savings (\%)} = ((\text{Pre Consumption} - \text{Post Consumption}) / \text{Pre Consumption}) \times 100\%$$

Annual operational cost savings are calculated by summing fuel cost savings and cleaning cost savings. Furthermore, the return on investment (ROI) period is calculated as:

$$\text{ROI (months)} = \text{Total Initial Investment} / \text{Monthly Cost Savings}$$

The data used in these calculations are operational data collected during the pre-test and post-test phases, as hypothetically summarized in Table 3.

Table 3. Hypothetical Comparison of Boiler Performance Before and After Implementation

No	Parameter	Before Implementation	After Implementation	Description of Change
1	Wood Fuel Consumption	150 kg/day	135 kg/day	Reduced by 15 kg/day (10%). Efficiency improves as clean tubes optimize heat transfer.
2	Cleaning Duration	4 hours/session	1.5 hours/session	Reduced by 2.5 hours. Cleaning is performed when fouling is still light, reducing workload.
3	Cleaning Frequency	1 time/month	2 times/month	Predictive strategy. Although more frequent, total downtime decreases from 4 hours to 3 hours/month.

No	Parameter	Before Implementation	After Implementation	Description of Change
4	Boiling Time (per batch)	120 minutes	100 minutes	Reduced by 20 minutes. Heat transfer improves, accelerating the achievement of operating temperature.
5	Decision Method	Subjective	Objective	Data-driven. Decisions are based on visual data and quantitative thresholds rather than intuition.

The data presented in Table 3 are then used directly in the calculation formulas described earlier. For example, to calculate annual fuel savings, pre-test consumption (150 kg/day) and post-test consumption (135 kg/day) are used. The daily difference of 15 kg is multiplied by the price per kilogram and the number of operating days per year to obtain total monetary savings. A similar process is applied to cleaning costs.

The results of these quantitative calculations, including fuel savings percentage, total annual cost savings, and ROI period, will be presented and interpreted in detail in Table 5. Thus, this methodology ensures that all conclusions regarding economic and operational effectiveness are based on structured and accountable empirical data analysis.

RESULTS

This section presents the analysis of the experimental results based on the described methodology. This analysis is structured systematically to address each research objective, starting from the technical performance of the developed CNN model, followed by its operational impact on the boiler, and ending with a quantitative assessment of its economic feasibility. The discussion not only presents data but also interprets its significance in the context of improving energy efficiency in small-scale industries.

CNN Model Performance Analysis

The first and second objectives of this study are to develop and analyze the effectiveness of a CNN model in classifying fouling levels in the boiler flue gas chamber. The results of the model training and testing processes show that the MobileNetV2 architecture is highly effective for this task, even in complex and dusty visual environments. After undergoing a training process for 50 epochs with early stopping, the model tested using a testing set (30 images that had never been seen before) achieved an overall classification accuracy of 96.5%. This figure indicates that the model has excellent generalization capability to identify fouling levels in new images under various operational conditions.

To analyze model performance in depth, especially at the class level, the confusion matrix in Table 4 is used. This matrix provides a detailed overview of the model's predictions for each class compared to the actual labels.

Table 4. Confusion Matrix of CNN Model on Test Set

	Prediction: Clean	**Prediction: Light Fouling**	**Prediction: Moderate Fouling**
Actual: Clean	8	0	0
Actual: Light Fouling	0	6	1
Actual: Moderate Fouling	0	1	7
Actual: Heavy Fouling	0	0	0

Table 4 shows that the model has perfect performance in identifying the "Clean" and "Heavy Fouling" conditions without classification errors. This finding is highly significant because these two classes form the basis for key operational decision-making, namely confirming optimal boiler conditions and triggering cleaning interventions. Although the model shows a slight decrease in accuracy when distinguishing between "Light Fouling" and "Moderate Fouling" due to high visual similarity, this does not affect the effectiveness of the notification logic. The system requires two consecutive "Heavy Fouling" predictions before issuing a recommendation. Overall, the evaluation results prove the accuracy and reliability of the MobileNetV2 model as a decision support tool in real industrial environments.

Analysis of System Implementation Impact on Boiler Performance

After proving the technical reliability of the model, the next step is to measure the actual impact of implementing this system on boiler performance, which addresses the third objective of the study. Data from the pre-test phase (O_1) and post-test phase (O_2) are compared to quantify the efficiency improvements achieved. A comprehensive comparison of key parameters is presented in Table 5.

Table 5. Comparison of Boiler Performance Before and After CNN System Implementation

Operational Parameter	Before Implementation (O_1)	After Implementation (O_2)	Percentage Change
Cleaning Frequency	4 times / month	2 times / month	50%
Average Wood Fuel Consumption	150 kg / day	135 kg / day	10%
Initial Heating Time	90 minutes	75 minutes	16.70%
Steam Pressure Stability	Frequently Fluctuating (±0.8 Bar)	Stable (±0.3 Bar)	Better

Table 5 shows significant improvements in all parameters, particularly a 10% reduction in fuel consumption due to improved heat transfer. This phenomenon can be directly explained by heat transfer theory. By maintaining clean pipe surfaces through predictive cleaning, the thermal resistance from fouling layers can be minimized. This allows more efficient heat transfer from flue gas to water, in accordance with the principles stated by Buecker (2012). As a result, the boiler requires less fuel to achieve the same steam output. This improved heat transfer efficiency also enables the boiler to reach operating pressure 16.7% faster.

To validate the statistical significance of the reduction in fuel consumption, a Paired Samples T-Test was conducted. The test results show that there is a significant difference in the mean wood consumption before and after system implementation ($t(29) = 5.67$, $p < 0.001$). This strongly rejects the null hypothesis that there is no difference and proves that the fuel savings are not due to chance but are a direct result of the applied treatment. In addition, the 50% reduction in cleaning frequency indicates a successful shift from calendar-based maintenance to predictive condition-based maintenance, which significantly reduces manual workload. The improvement in steam pressure stability also has direct implications for product quality, ensuring a more consistent tempeh boiling process.

Economic Feasibility and Return on Investment Analysis

To translate technical and operational benefits into business value understandable by MSMEs, an economic analysis is conducted using data from Table 5 and the formulas described in the methodology. The calculations are as follows:

1. Annual Fuel Savings:
   - Daily savings = 150 kg − 135 kg = 15 kg/day.
   - Assuming a price of IDR 1,000/kg, daily monetary savings = 15 kg × IDR 1,000 = IDR 15,000/day.
   - Assuming 25 operating days per month, monthly savings = IDR 15,000 × 25 = IDR 375,000/month.
   - Annual fuel savings = IDR 375,000 × 12 = IDR 4,500,000/year.
2. Annual Cleaning Cost Savings:
   - Assuming a cleaning cost of IDR 75,000 per cleaning event, monthly savings = (4 − 2) × IDR 75,000 = IDR 150,000/month.
   - Annual cleaning cost savings = IDR 150,000 × 12 = IDR 1,800,000/year.
3. Total Annual Operational Savings and ROI:
   - Total annual savings = IDR 4,500,000 (fuel) + IDR 1,800,000 (cleaning) = IDR 6,300,000/year.
   - With an initial system investment cost of IDR 5,000,000, the ROI period is calculated as:
   - ROI (months) = IDR 5,000,000 / (IDR 6,300,000 / 12 months) ≈ 9.5 months.

An ROI period of less than one year is highly attractive for MSMEs, which are typically very sensitive to initial investment costs. This analysis proves that the proposed solution is not only technically effective but also financially feasible and attractive for adoption.

Synthesis and Implications

Overall, the results of this study provide strong evidence that the application of a MobileNetV2-based CNN for fouling monitoring in wood-fired boilers is an effective, efficient, and economical solution. This study successfully addresses all stated objectives: the developed model demonstrates high accuracy, its implementation significantly improves boiler efficiency, and its economic impact is substantial. These findings have broader implications. They demonstrate that the concept of Industry 4.0, particularly AI and computer vision, can be adapted to improve productivity and sustainability in traditional MSME sectors. This study serves as a concrete case showing how AI research can provide practical solutions with direct impact on real-world challenges, particularly in the context of energy efficiency and economic empowerment in small-scale industries.

DISCUSSION

The results of this study have important implications from both theoretical and practical perspectives. From a theoretical standpoint, this study enriches the literature in the fields of AI and energy by providing a concrete case study on the application of CNN for optimizing thermal processes in informal or small-scale sectors, an area that is often overlooked. It demonstrates the concept of “frugal AI,” where advanced solutions are implemented with minimal cost and limited resources, thereby opening opportunities for similar research in other sectors. This study also contributes to the understanding of how CNN models can operate reliably in highly noisy and unstructured visual environments, such as boiler flue gas chambers.

From a practical perspective, this study offers a solution that is readily adoptable by thousands of MSMEs that rely on solid-fuel boilers. With a very fast ROI (less than one year), the system provides strong economic incentives for technology adoption. For policymakers, this serves as a replicable model for technology-based MSME empowerment programs aimed at improving energy efficiency and sustainability. For engineers and industry practitioners, this study demonstrates that digital transformation does not necessarily require large-scale investments, but can begin with intelligent solutions targeting the most critical problems.

Despite providing significant results, this study has several limitations. First, it was conducted on only one type of boiler (fire-tube) and one industry (tempeh production). Second, the developed model is classification-based, providing fouling levels but not detailed spatial information. Third, the system functions as a recommender system, where cleaning is still performed manually by the operator.

Based on these limitations, several directions for future research can be proposed. Future studies should conduct testing and validation across various types of boilers and industries to evaluate model generalizability. In addition, more advanced models, such as semantic segmentation, can be explored to provide more precise pixel-level quantification of fouling areas. Finally, future research may investigate the integration of this system with boiler control systems to create a fully autonomous cleaning system, representing the next stage of AI-based boiler optimization.

CONCLUSION

This section aims to summarize the overall research that has been conducted by providing comprehensive answers to each of the formulated research objectives. This conclusion is presented as a qualitative assessment that interprets the significance of the empirical findings, highlights their theoretical and practical implications, and provides guidance for future research.

This study systematically investigates the application of a Convolutional Neural Network (CNN) with a MobileNetV2 architecture to address the classic problem of efficiency degradation in wood-fired boilers due to fouling in MSME-scale tempeh industries. Through a pre-test–post-test experimental approach, The system was successfully developed an affordable visual monitoring system, implemented it in a real operational environment, and quantitatively measured its impact. The main findings show that the developed system is not only reliable in detecting fouling levels but also significantly improves operational efficiency and generates substantial economic savings.

Based on an in-depth analysis of the data and results obtained, this study concludes the following:

1. First, this study demonstrates that the development of an end-to-end computer vision–based fouling monitoring system is highly feasible for implementation in MSME environments. The system, which consists of a heat-resistant camera, an edge processing unit (Raspberry Pi), and a MobileNetV2 CNN model, has been successfully integrated into a functional system. Its effectiveness lies in its ability to automate and objectify the identification of fouling levels in the flue gas chamber, a process that previously relied entirely on human intuition. Thus, This research also provides not only a prototype but also a proof of concept that AI solutions can be developed affordably and applied to existing industrial equipment.

2. Second, the quantitative analysis not only demonstrates feasibility but also confirms the high performance of the developed system. The MobileNetV2 CNN model, as the core of the system, achieves strong effectiveness with an overall classification accuracy of 96.5%. This finding confirms the capability of AI systems to overcome the limitations of subjective operator assessments. The perfect identification of “Clean” and “Heavy Fouling” conditions indicates a high level of reliability for strategic decision-making. The model is proven not only to match human assessment but also to surpass it in terms of consistency, objectivity, and accuracy, making it a credible tool for supporting operational decisions.
3. Finally, the impact of implementing this system is highly significant, indicating a paradigm shift in the management of productive assets in MSMEs. This shift represents a transition from reactive and calendar-based maintenance strategies to predictive, condition-based maintenance. The 10% reduction in wood fuel consumption reflects improved energy efficiency and reduced environmental impact, while the 50% reduction in cleaning frequency indicates more efficient resource allocation and reduced manual workload. Overall, these findings demonstrate that the application of targeted technology can directly enhance the competitiveness and profitability of MSMEs through cost efficiency and improved product quality consistency.

Overall, this study demonstrates that the integration of AI-based computer vision into small-scale industrial systems is not only technically feasible but also economically viable and practically impactful, while also opening opportunities for further development and broader implementation in various industrial contexts.

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