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# Rule-based Automated Waste Detection for Industry 4.0

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## Abstract

Managing waste effectively is very important in industries to save resources and reduce costs. Traditionally, the identification of waste has relied on manual inspection, which is time-consuming, costly, and susceptible to human error. This is especially problematic in factories where production lines change often, making manual waste checks even more costly. In response to these issues, this paper introduces a novel approach aimed at automating the process of waste detection. We propose a structured repository of rules designed to categorize industrial activities into eight distinct waste categories. The development and validation of these rules are detailed, and their implementation has been tested in the Fischertechnik learning factory environment. Results demonstrate that our rule-based system not only achieves high accuracy in identifying waste types but also significantly reduces the time and costs associated with waste detection processes. This research represents a progressive step towards the automation of waste detection in industrial settings, promising substantial improvements in efficiency and reduction in operational costs.

## Keywords
Industry 4.0; Industrial Internet of Things (IIoT); Value Stream Mapping; Value Creation; Waste Detection.

## 1. Introduction
In the era of Manufacturing 4.0, automation stands as the cornerstone of innovation, reshaping traditional paradigms and driving unprecedented efficiency in industrial processes. At the heart of this transformation lies the development of highly automated value stream analysis techniques, poised to revolutionize the manufacturing landscape. These techniques represent not just a technological advancement, but a critical response to the pressing need for enhanced efficiency and productivity in today's competitive markets.

Waste detection or respectively added value detection is a key activity in value stream analysis. This task mainly consists in classifying any resource use into either added value, or non-added value, or necessary non-added value. This activity is currently insufficiently automated. Manual waste detection suffers from many challenges that limit its efficacy in modern manufacturing environments. From time-intensive procedures to subjective interpretations, the limitations of manual processes are increasingly evident, particularly in dynamic production settings characterized by rapid changes and evolving demands. Furthermore, the scalability and adaptability of manual methods pale in comparison to the evolving complexities of contemporary manufacturing operations.

In contrast, automated waste detection techniques would offer a paradigm shift in waste management, leveraging cutting-edge technologies to navigate the complexities of modern production processes with unprecedented speed and accuracy. By harnessing the power of data analytics and machine learning algorithms, automation of wate detection not only streamlines waste identification but also mitigates the inherent biases and inconsistencies associated with manual approaches. Furthermore, when planning new production lines, the integration of these techniques allows for the precise measurement and analysis of added value, non-added value, and necessary non-added value. This crucial evaluation enables companies to minimize non-added value and strategically select the optimal use of resources (e.g., combination and configuration of machines) for the new production line, ensuring minimal waste and enhanced resource efficiency from the outset.

This paper delves into the challenges of manual waste identification, highlighting the imperative for automation in addressing these limitations. Moreover, it explores the transformative potential of automated systems, examining their implications for enhancing efficiency, minimizing waste, and bolstering competitiveness in the manufacturing industry. As manufacturing increasingly embraces automation to stay ahead in today's dynamic market landscape, the integration of automated waste detection solutions emerges as a cornerstone of sustainable growth and innovation.

In this work, we aim to develop an automated, end-to-end solution that not only identifies but also quantifies industrial waste. Our contribution includes the creation of a novel, rule-based repository that systematically categorizes waste. We implement and test our technique within the Fischertechnik learning factory environment. This approach not only significantly reduces the associated time and costs but also enhances the accuracy of waste detection, demonstrating a substantial improvement over conventional manual inspection methods in industrial settings.

The remainder of this paper is structured as follows. Section 2 discusses related work Section 3 presents the Preliminaries, which contain foundational principles. Section 4 details the system model and assumptions. Section 5 describes the proposed solution. Section 6 provides the evaluation. Finally, the Conclusion summarizes the findings and suggests avenues for future research.

## 2. Related Work

In 2016, Grzelczak and Lewandowsky embarked on a significant research endeavor aimed at identifying and evaluating waste across various industries. Their study involved surveying 1050 employees spanning different sectors, including manufacturing, commercial, service, and administrative units. The findings were revealing, highlighting pressing issues such as underutilized employee potential, unnecessary transport, and improper processing as key areas needing attention. Surprisingly, respondents seemed to downplay overproduction, excess inventory, and defects, possibly owing to the prevalence of Just-in-Time (JIT) principles and Total Quality Management (TQM). However, despite the thoroughness of their analysis, it's essential to note a significant limitation: the entire process was conducted manually. This manual approach, while yielding valuable insights, undoubtedly introduced inefficiencies and limitations, potentially hindering the depth and accuracy of the study's findings. Therefore, while Grzelczak and Lewandowsky's research shed light on critical aspects of waste management, the reliance on manual methods underscores the need for more automated and streamlined approaches in future investigations.

In 2019, a study titled "Identification of Waste in Shipping Operational Processes Using VSM (Value Stream Mapping)" was conducted. This paper explores waste analysis within the shipping operational process, aiming to reduce departure delays by 60%. The analysis targets operational factors like creating checklists, vendor selection, and item grouping based on customer identity. However, the study is limited to examining only two types of waste: waiting and motion.

In 2020, a case study conducted in three multinational fast-food companies in Madrid, Spain, aiming to identify Muda (waste) in the fast-food service industry. Seven types of Muda were identified, including defects, movements, process inefficiencies, inventory issues, overproduction, transport inefficiencies, and delays. Practical implications for practitioners and managers are discussed, emphasizing waste identification as a means for process improvement. However, the qualitative nature of the data limits generalizability, findings are specific to hamburger fast-food restaurants in Spain, and Muda identification relied on customer perspectives due to the unavailability of internal process data.

In May 2023, a case study onIdentification of waste in electricity transmission infrastructure projects using Value Stream Mapping was conducted in the 500 kV Sumatera Package 3 transmission project, focusing on waste identification and reduction. The study utilizes Value Stream Mapping (VSM) to pinpoint non-value-added activities and propose enhancements for waste minimization, in line with lean manufacturing principles. It underscores the importance of optimizing planning and production systems to bolster organizational efficiency. However, certain limitations are noted. Firstly, the study focuses on the 500 kV Sumatera Package 3 transmission project, which may limit the generalizability of the findings to other types of project. Additionally, the identification of waste in the project relies on the perception and input of personnel involved in the project. This subjective nature may introduce bias or overlook certain types of waste that are not apparent to the personnel.

## 3. Preliminaries

### 3.1 The Toyota Production System (TPS)

TPS is founded on a vision articulated by Taiichi Ohno, aiming to fulfill transportation needs while minimizing resource use and environmental impact, thus maximizing value for customers and society. TPS emphasizes responding to necessity, with Taiichi Ohno tasked by Eiji Toyoda to enhance domestic production processes despite resource limitations compared to Ford. TPS principles include adapting production to customer demand, employing the pull principle from American supermarkets, maintaining smooth production flow with JIT methodology, and focusing on error prevention, continuous improvement, and eliminating non-value-added activities. By the 1990s, TPS gained global recognition, evolving beyond cost reduction to prioritize product quality. TPS is not merely about applying principles but entails the entire system's interaction, motivating and supporting employees in continuous process optimization and improvement.

### 3.2 Waste Model

Waste in the context of the Toyota Way refers to everything that does not directly contribute to value creation and thus wastes resources. This can be in manifest in various forms, such as excessive inventory, unnecessary transportation, Waiting times or defects in products. The goal is to eliminate these types of waste, identify and eliminate waste to improve efficiency and cost-effectiveness and ultimately increase customer value. As part of the TPS, it is crucial that to identify and eliminate important types of waste, as suggested by Taiichi Ohno described. These wastes.

By thoroughly analyzing and eliminating these wastes Companies can optimize their production processes and use their resources more effectively. Overproduction, for example, leads to unnecessary inventory and increases the risk of losses due to obsolete products or changes in demand. Waiting times arise often due to inefficient processes or interruptions in the production flow productivity impaired. Eliminating these wastes requires a thorough analysis of the entire Value chain and continuous improvement of processes. Toyota has shown that the consistent application of these principles results in high efficiency and quality can be achieved, ultimately leading to lower costs and higher customer satisfaction. Table 1 shows some examples of the eighth types of waste.

Table 1. Examples of the 8 Types of Wastes

| Waste Category | Examples |
|---|---|
| Transportation | Material transfer, multiple handling |
| Inventory | Excess safety stock, excess inventory |
| Motion | Unnecessary worker movement |
| Waiting | Slow pace handling, excess queue |
| Overproduction | Producing more than required |
| Over processing | Inappropriate processing steps |
| defects | Out of specifications, scrap, rework |
| Unused Talent | not encouraging workforce creativity |

### 3.3 Value Creation

Lean principles focus on creating value from the customer's perspective by understanding customer needs, designing products accordingly, optimizing processes Improve process capability, organize value-adding steps, a continuous one Establish flow, implement pull systems and continuously improve the value chain.
In lean manufacturing, activities are divided into three main categories to increase efficiency and minimize waste:

- Value-added (VA) activities refer to actions that enhance a product's value, leading customers to be willing to pay for them. They involve tasks that physically change the product and move it closer to completion from the customer's perspective. For an activity to be considered value-adding, it must meet three criteria: (1) It must move the product closer to completion, (2) it is done correctly the first time without needing to be redone, and (3) the customer is willing to pay for it.
- Non-value-adding (NVA) activities, on the other hand, are tasks that do not contribute to the product's value or service improvement and are therefore not considered valuable by the customer. Although they take up time, they do not enhance the product or service quality. It is important to identify and eliminate these unnecessary activities so that time can be freed up for more meaningful improvements. For example, inspections are necessary to ensure quality but take up time and resources until automated testing methods are introduced, without directly increasing the end product's value.
- Necessary non-value-added (NNVA) activities are akin to unavoidable minor obstacles in the production process. They may not directly benefit the customer, but they are still essential for product manufacturing unless there is a fundamental redesign of the process. These tasks can potentially be eliminated in the long term, but it's unlikely in the short term. For instance, maintaining high inventory levels may be necessary to address unforeseen shortages, which may decrease over time as the production process stabilizes.

### 3.4 Value Stream Mapping

Value Stream Mapping (VSM) is a lean manufacturing technique used to visually represent and analyze the flow of materials and information required to bring a product or service from its initial concept to the customer's hands. It involves creating a detailed map of all processes involved in delivering a product or service, including both value-adding activities and NVA activities (such as delays or waste). The purpose of VSM is to identify areas of inefficiency, waste, and bottlenecks within the process in order to streamline operations, improve quality, and reduce lead times. It serves as a powerful tool for continuous improvement and optimization within organizations.

## 4. System Model

*VSM Model*: We consider a production line that has been modeled using a VSM model by an expert.
*Data Collection*: Data about the production line, the production processes and the ongoing manufacturing are collected and provided in advance, enabling the recording of relevant information necessary for value stream analysis. The collected data serves along with the VSM to visualize and analyze processes effectively.
*Focus on Recognized Waste Types*: The model assumes that the analysis will focus exclusively on the seven types of waste identified in lean management, excluding 'underutilized talent' due to the complexities involved in accurately identifying and quantifying this type of waste within operational processes.
*Machine-readable Format*: Data must be in a machine-readable format specifically designed for VSM. This ensures efficient processing and enhances the accuracy and effectiveness of the system.
*Data Representation*: The data representation model uses JSON format to log activities in a manufacturing process, providing a detailed account of each operational step. Here is a detailed explanation of the data structure:

- Activity List: Data is structured as a list, where each entry represents an activity performed sequentially in the production process. Each activity is encapsulated in a JSON object, which includes details such as the machine used, the activity type, and the start and end times.
- Machine Information: Each activity is linked to a specific machine, indicated by the machine name field. This field identifies which machine performed the activity.
- Activity Details: The type of activity is specified in the activity name field.
- Time Stamps: The start time and end time fields mark the beginning and end of each activity, providing precise time tracking.
- Additional Data: A databox field may contain extra details pertinent to the activity, such as current demand (current demand for the product), produced units (number of units produced during the activity), optimal processing steps (optimal number of processing steps required), processing steps (actual number of processing steps taken), optimal steps (optimal total steps for the activity), number of steps (actual total steps taken), defect (error rate during the activity) (if applicable), inventory level (inventory level at a specific time), optimal inventory level (optimal inventory level).

This structured JSON format enables the system to accurately process and analyze the information for optimization and monitoring purposes. Adherence to this format is crucial for maintaining data integrity and consistency, which are essential for effective system functionality and achieving optimal results in manufacturing process optimization.

## 5. Solution

In the following, we propose a new solution to facilitate the automated recognition of value and waste in manufacturing processes.

### 5.1 Overview on Our Approach

Our solution parses and analyzes activity data stored in a structured JSON format, containing crucial information such as timestamps, defects, inventory levels, demand, units produced, and optimal processing steps (Section 4) (Figure 1).

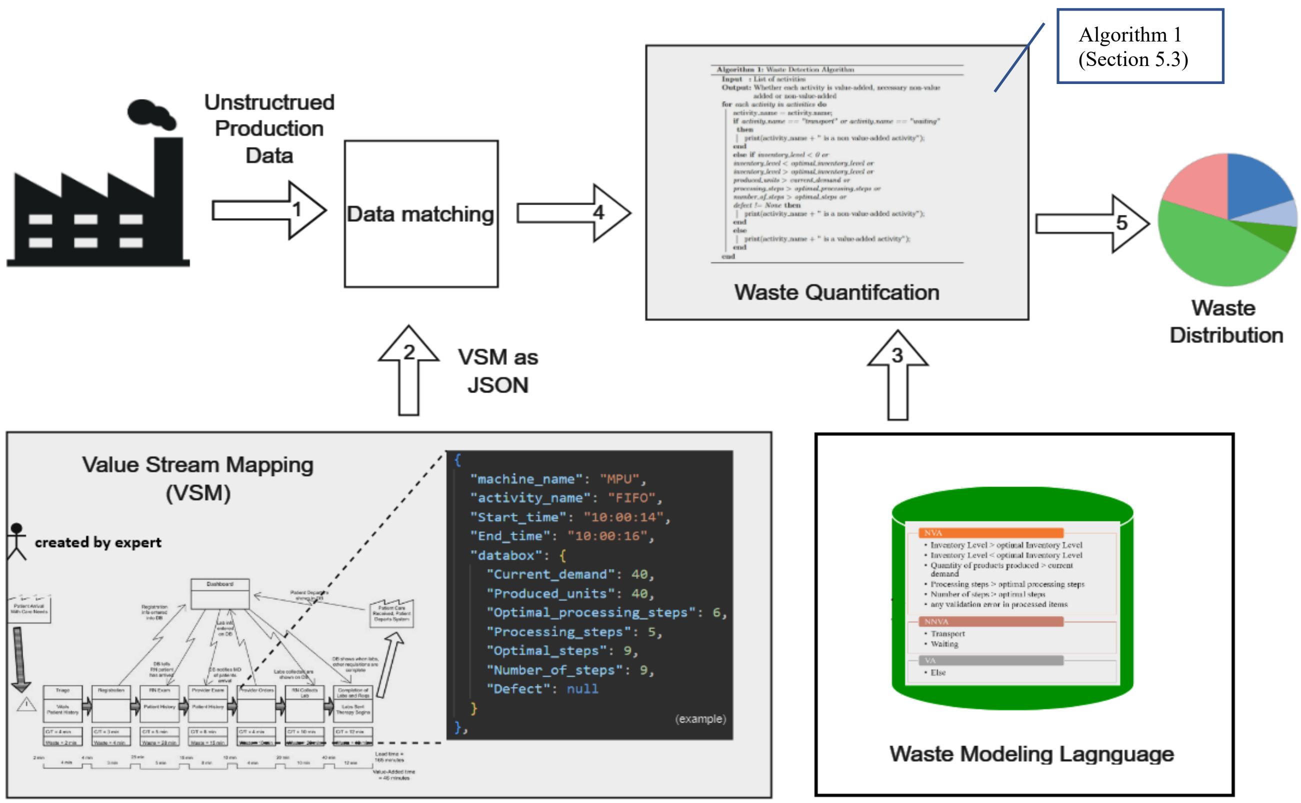



Figure 1. Key Components and Steps of the Proposed Solution

The process begins with the collection of unstructured production data from the factory (Step 1). This data is then matched and converted into a structured format, specifically Value Stream Mapping (VSM), represented as JSON (Step 2). The JSON-formatted VSM is processed using a Waste Modeling Language (Step 3) to identify and classify different types of waste, such as NNVA and VA activities. The waste quantification algorithm (Step 4) evaluates each activity against predefined criteria to determine its contribution to waste. Finally, the results are visually represented in a waste distribution chart (Step 5), highlighting the proportions of various types of waste within the production process. This comprehensive approach facilitates targeted improvements in efficiency by providing clear insights into waste sources and their impact on manufacturing performance.

### 5.2 Waste Rules Repository

Classify activities according to waste rules:

- Errors and defects: The solution checks for defects, updating the activity's final status to indicate it as NVA if defects are present.

- Warehousing: It evaluates whether inventory levels align with value creation. Deviations from optimal levels are flagged as NVA.
- Overproduction: The solution compares the number of units produced with current demand, identifying overproduction as NVA.
- Over processing: It compares the number of processing steps to the ideal steps, detecting over processing as NVA.
- Movement: The solution compares the number of movements to the recommended steps, identifying unnecessary movements as NVA.
- Consideration of "waiting" and "transport": The solution accounts for "waiting" and "transport" activities, recording their durations as NNVA time, as these activities are not value-adding but are part of the process.

Figure 2 summarizes the workflow and key aspects of the solution.

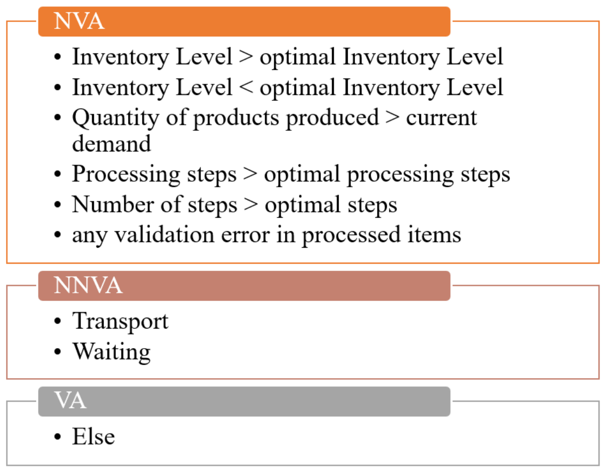



Figure 2. Rules Repository

### 5.3 Waste Detection Algorithm

Clarification on the implementation details can be found in Algorithm 1. The proposed algorithm automates the process of classifying activities within a VSM model. It takes a VSM model as input and iterates through each activity present within the model. Two initial conditions are used to classify an activity as NVA:

- If the activity's name is "transport" or "waiting," then it's classified as aNVA activity.

These activities are generally considered to be NVA because they do not alter the physical state of the product.
If none of the above conditions are met, the algorithm checks for several other conditions to classify an activity as NVA:

- Inventory level lower than zero.
- Inventory level lower than the optimal level or exceeding the optimal level.
- Produced units exceeding the current demand.
- Processing steps exceeding the optimal number of steps.
- Number of steps surpassing the optimal limit.
- Presence of defects.

These conditions indicate potential inefficiencies or areas for improvement within the process. For instance, an inventory level lower than zero suggests insufficient stock to meet demand, which can lead to production delays. If any of these conditions are true, the activity is classified as NVA. Otherwise, the activity is classified as a value-added activity.

```
Algorithm 1: Waste Detecion Algorithm
Input :VSM_Model
Output :Whether each activity is value-added,
  necessary non-value-added or non value-added
foreach activity in VSM_Model do
    if activity_name == transport or
     activity_name == waiting then
        print(activity_name + "is a necessary
          non-added-value-activity");
    end
     else if  Inventory_level < 0 or
     Inventory_level < optimal_inventory_level or
     Inventory_level > optimal_inventory_level
     or Produced_units > current_demand or
     Processing_steps > optimal_processing_steps
     or Number_of_steps > optimal_steps or
     defect != None then
        print(activity_name + "is a
          non-added-value-activity");
    end
     else  print(activity_name + "is a
     value-added-activity");
end
```

Algorithm 1. Waste Detection Algorithm

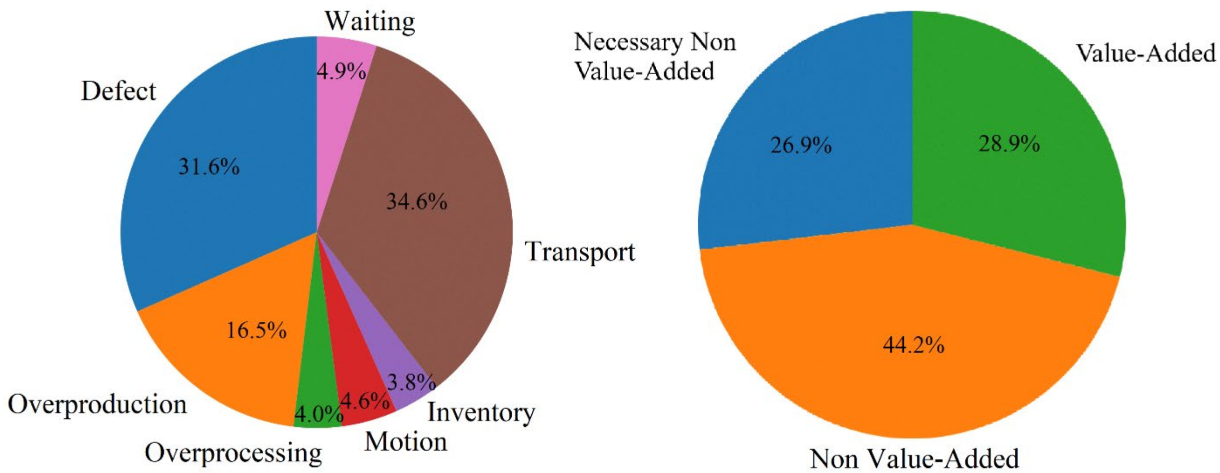
# 6. Evaluation

## 6.1 Experimental Setup

We now evaluate our proposed solution at the example of Fischertechnik Learning Factory. This factory is an educational tool designed to teach automation, mechatronics, and industrialmanufacturing principles.The factory consists of fivemain components, the vacuum suction gripper (VGR), theautomated high-bay warehouse (HBW), a multi-processingstation with a kiln (MPO), a sorting line with color recognition(SLD), the environmental station with surveillance camera(SSC) and an output station with color recognition andNFC reader (DPS). The SSC was not evaluated in this analysis since it requires human intervention.

## 6.2 Results and Discussion

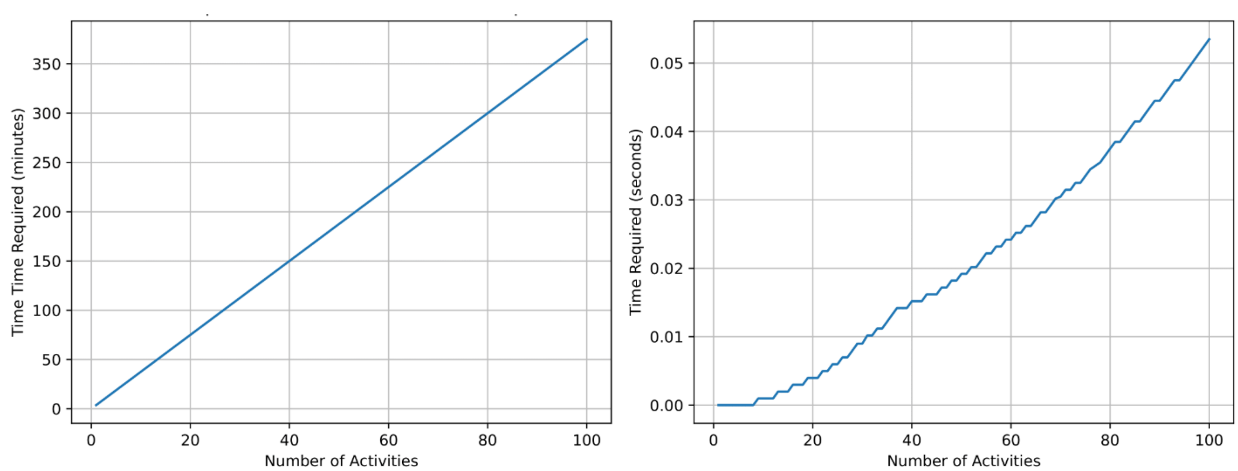
The analysis of the collected data demonstrates how the automated detection system adeptly identifies waste within manufacturing processes, allowing for the testing of our system's efficacy. Utilizing structured data in VSM format ensures efficient processing and analysis, thereby facilitating improvements in efficiency and productivity within the manufacturing industry. Moreover, the presentation of results through visual aids enhances comprehension. Two pie charts are generated from the data: The first illustrates the distribution of activities into VA, NVA, and NNVA categories, while the second provides a detailed breakdown of the percentage of each waste type present in specific activities (Figure 3).




(a) Value Distribution (b) Waste Classes

Figure 3. Value and Waste Distributions

After conducting several direct comparison studies, we obtained the results of our automated model compared with those of an expert performing the same tasks manually. These experiments were conducted using data for 100 activities. Assuming that the expert is familiar with the 7 rules of waste and possesses a clear understanding of how to interpret the provided JSON data, along with the data being well-structured and easily interpretable, the expert would follow a systematic approach for each activity, as outlined in Figure 5. Based on these assumptions and considering the variability in the complexity of each activity, the estimated time for an expert to apply all the rules to a single activity would be approximately one minute. This assessment includes reading and understanding the activity details, applying waste rules, and identifying any existing waste (Figure 4).




(a) Expert (b) Our Approach

Figure 4. Time Required vs. Number of Activities

In our experiment, we analyzed the error rates in waste detection through both our automated approach and manual assessment by a single expert. The results demonstrate that our automated model consistently operates error-free when the specified conditions are fulfilled. Conversely, manual detection by a human expert introduces the potential for errors, as depicted in Figure 5, where an expert can make approximately 0.06 errors per 100 activities. Despite these occasional errors, our automated approach maintains a high level of reliability and consistency.

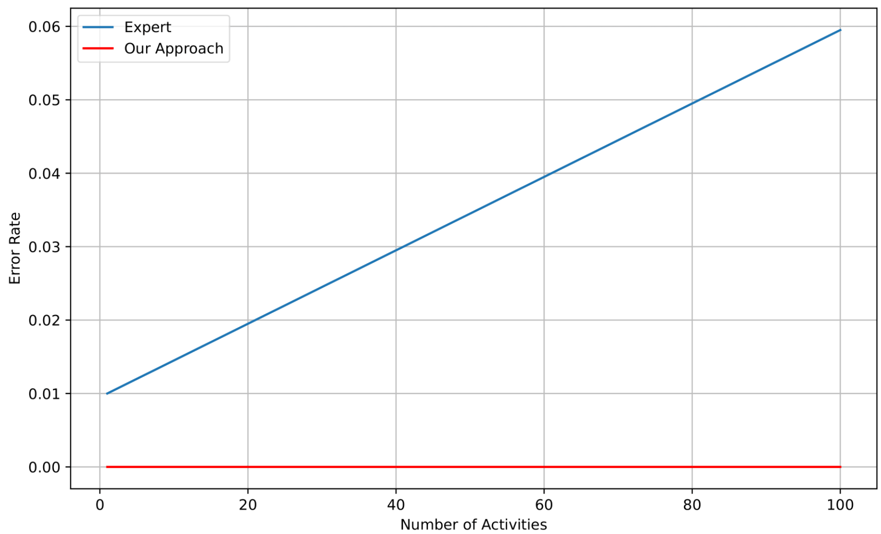



Figure 5. Error Rate vs. Number of Activities

Based on these results, it can be seen that our approach is significantly more efficient in terms of time is because the automated model performs the tasks faster and more consistently Comparison to manual methods by an expert.

## 7. Conclusion

The automated detection system for identifying waste in Manufacturing processes, implemented with structured data in VSM format, proves to be as a significant advance in the optimization of industrial processes. The precise Identification of waste and the optimization measures based on it, supported by visual representations of the results, offer an efficient way to Increasing efficiency and productivity in the manufacturing industry.

The direct comparison of our automated solution with manual methods by experts shows significant time savings and consistency advantages. While a Experts need about a minute per activity to set the waste rules manuallyour system can do this faster and error-free at the same time. This Improving efficiency is crucial, especially in environments where time and resources are scarce.

Furthermore, experiments have shown that our automated model is error-free works as long as the data meets the required conditions. In contrast to There is always a human risk when carried out manually by experts Failure, even if minimal. This highlights reliability and consistency our solution compared to traditional approaches.

Overall, our approach provides an innovative and effective method for dealing with Waste in manufacturing processes. By combining automation, with precise data processing and visual representation, companies can do more than just their Increase productivity, but also strengthen your competitiveness and reduce costs.

## References

Ajit Kumar R. Girish Kumar N.S. Narahari K.M. Mithilesh. Case study on identification and elimination of waste through lean implementation in an automotive part manufacturing industry. *International Journal of Lean Enterprise Research*, 2015.

Ayu, Endah, Wahyuni., Amin, Rais. "Identifikasi Waste Pada Proses Operasional Shipping Dengan VSM (Value Stream Mapping) Pada PT XYZ."*jurnal Teknik industri*,2019.

Bowen, D.E. and Youngdahl, W.E., "Lean" Service: in Defense of a Production-Line Approach*", International Journal of Service Industry Management*, Vol. 9 No. 3, 1998.

Dickmann, P., Schlanker Materialfluss: mit Lean Production, Kanban und Innovationen, (3rd Edition.). Grafing, Germany: Springer Vieweg, 2015.
FischertechnikLernfabrik 4.0 accompanying booklet version 6, 2023.
George, M.L., Lean Six Sigma for Service: How to Use Lean Speed and Six Sigma Quality to Improve Services and Transactions, McGraw-Hill, New York, NY, 2003.
Grace Simamora and Mona F Toyfur and HeniFitriani.Identification of waste in electricity transmission infrastrture projects using Value Stream Mapping,*Jurnal Mitra Teknik Sipil*, 2023.
Grzelczak A. and Werner-Lewandowsky, K., Eliminating Muda (Waste) in Lean Management byWorking Time Standardization *Faculty of Engineering Management*, Poznan University of Technology, Poland, 2016.
Koning, H., Verver, J.P., Heuvel, J., Bisgaard, S. and Does, R.J. , "Lean six sigma in healthcare*", Journal for Healthcare Quality*, Vol. 28 No. 2, 2006.
Lander, E. and Liker, J.K., The Toyota Production System and Art: Making Highly Customized and Creative Products the Toyota Way, *International Journal of Production Research*, 2007.
Manuel Francisco Morales-Contreras Manuel F. Su ́arez-Barraza Marcelo Leporati. Identifying Muda in a fast food service process in Spain, *International Journal of Quality and Service Sciences*, 2020.
Martin and Osterling. *Value Stream Mapping: How to Visualize Work Flow and Align People for Organizational Transformation*, 1st Edition **,** McGraw Hill**,** 2013.
Nurlaelah, Nurlaelah, Value stream mapping for waste identification in the low-cost house construction process (case study: xyz housing.*International Journal of Civil Engineering and Infrastructure (IJCEI),* 2023.
Ono, T., Toyota Production System : Beyond Large-Scale Production, 1988.
Sunder, M.V., Ganesh, L.S. and Marathe, R.R. , "A morphological analysis of research literature on lean six sigma for services", *International Journal of Operations and Production Management*, Vol. 38 No. 1, 2018.
Walters, L., Nickerson, M. and Hall, L., "Improving the 1040 process by applying lean principles: a case study", *The TQM Journal*, Vol. 32 No. 2, 2019.

## Biographies

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