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REAL-TIME DETECTION OF SHREDDER CLOGS USING SUPERVISED ANN FOR PREDICTIVE MAINTENANCE

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ABSTRACT

Industrial waste shredders are often subject to clogging with bulky or entangled materials that induce reverse motor events, which can lead to an increase in wear and loss of production. This work introduces a supervised artificial neural network (ANN)-based system for detecting clog-prone waste in real time based on a relationship between the visual content of a camera mounted on a shredder and motor reversal behavior. The model was trained with supervised data on 400 manually annotated images and achieved 92% accuracy with a 0.5 second alert time in real-time validation tests. As a proof-of-concept system, it is well suited for long-term data collection and is a strong candidate for implementation in predictive maintenance of the equipment. The flexible architecture is also relevant in other industrial settings that can pair visual and mechanical signals with negative events.

Keywords: Shredder Clog Detection, Predictive Maintenance, Supervised ANN, Industrial Waste Processing, Reverse Motor Events, Real-Time Monitoring.

1. INTRODUCTION

Shredders are a crucial part of preprocessing bulky industrial waste that broke into processable sized waste that stores inside waste pits before going through burning and melting. Industrial waste treatment plants have the capacity to handle this bulky industrial waste than the medium of small-scale cleaning centers that operated by local municipalities. This in turn explains why local municipalities apply strict rules for garbage disposal from the perspective other than recycling.

In this research, shredding large, bulky material is addressed for industrial waste treatment plants. Same technology is readily applicable toward small to medium scale plants as well. At that time, it is a matter of downscaling that does not have many issues on implementation. On the other hand, if a down scaled solution is applied to in upscaling the parameters often suffer additional errors. This is a well-known factor in engineering design as system.

Focusing on large sized waste materials or having irregular shapes. These machines are designed to handle tough jobs, but one recurring problem is clogging. If the trash is too big or tangled, if it's made of mixed material, then shredded blades will get clogged. A short backward step of the motor to evacuate the occlusion is produced by the system as a reaction. While this automatic reversing provides some protection, frequent clogs can interrupt production, cause wear on equipment, and result in expensive downtime.

To the best of our knowledge, manual observation and basic thresholding on sensors are still largely employed in these facilities for identifying such events. These approaches can also be helpful but are still within their basic machine centered, in other words with bare-minimum built-in triggers. The real technical potential comes when those triggered alarms are properly interfaced with artificial intelligence. One such feature is that the current setup mostly fails to indicate which waste categories are potentially problematic or how to use these triggers effectively to aid long-term maintenance planning.

This work aims to offer a smarter approach. Adopting the supervised machine learning method, the system is trained to identify visual patterns in waste items which are often led by clogging problems. It does so by using video of the shredder overhead and tying it to motor behavioral data especially, the times in which the shredder backs up while clearing a jam. This is the time that shredder motors run in opposite direction for a short period of time with an alarm pulse.

By correlating visual data with reverse motor events, the system can detect clog-prone items in real time. Information on clog causing material, machine specific data are recorded and analyzed for predictive maintenance planning, allowing operators to anticipate issues, adjust workflows, and schedule maintenance more effectively. The result is a safer, more efficient, and more reliable waste processing environment.

2. LITERATURE REVIEW

Artificial Neural Networks (ANNs) are becoming more prevalent in the realm of industrial automation, particularly for tasks such as predictive maintenance and fault detection. Most cases of AI based predictive maintenance is done on specific part of a machine rather than on a system. The reason is the inherent complexities as a system. Following are some resent impressive advance achievements by scholars for our enthusiastic readers.

Their capability to discern intricate patterns from sensor and image data enables them to effectively recognize early indicators of equipment malfunctions, such as blockages in waste shredders. In a comprehensive review, Garcia et al. highlighted various predictive maintenance approaches for industrial machinery. They underscored the importance of integrating real-time monitoring with machine learning techniques to foresee mechanical failures prior to their manifestation [1].

Jadhav et al. examined several machine learning algorithms for predictive maintenance, including ANN, LSTM, and Random Forest. Their study showed that supervised learning models can effectively process sensor data to forecast equipment degradation and remaining useful life, which is essential for planning maintenance in demanding environments [2].

Haque et al. explored the role of IoT sensors and AI algorithms in predictive maintenance. Their findings support the use of ANN frameworks for condition-based monitoring, particularly in systems where mechanical feedback, such as motor reversal, can signal operational issues [3].

Baradaran applied supervised learning models to electric motor diagnostics, classifying operational states such as healthy, maintenance-needed, and faulty. This approach is relevant to clog detection in shredders, where reverse motor events indicate a shift from normal operation [4].

Rakib Sayem et.al. [5] created a deep learning system to better classify waste, aiming to make processing more efficient. While they mainly focused on identifying different materials, their approach also shows how image-based neural network models can be applied in waste management settings.

Although many studies emphasize how artificial neural networks can be used for industrial diagnostics, most of these are about predicting faults through sensors or sorting materials. Not many have tackled the real-time detection of shredder jams, and even in such a case fewer have advanced toward predictive maintenance.

This research proposes a new framework that blends image classification with monitoring of motor events by using supervised artificial neural network to spot clog causing waste even before it enters. This ability makes the system shift from simply reacting to faults to predictive one. It helps maintenance teams by revealing patterns that often lead to reversals or jams, so operators can divert the feeder conveyer lines early, avoiding damage and downtime. This is attractive feature obtained from short time data. On the other hand, long time data will be used in predictive maintenance.

By linking the visual features of waste with how the machine responds mechanically, this research offers a practical, data-driven tool for predictive maintenance in industrial waste shredding operations.

3. SYSTEM ARCHITECTURE AND METHODOLOGY

The following section describes how the proposed system is constructed and how it functions. Since the aim is to detect clog-prone waste before a full blockage occurs, allowing operators to respond early and plan maintenance more effectively.

3.1 System Overview

The proposed system can be divided into two sets of goals. One is a short-term goal as below and then a long-term goal of AI assisted maintenance planning. First phase of short-term goal is achieved and the latter the long-term goal can be realized only after accumulation of long-term data which is under development.

The system consists of three main components: a camera placed above the shredder inlet, a motor control unit that records reverse movements, and a supervised artificial neural network (ANN) that analyzes the data.

As waste enters the shredder, the camera captures continuous video footage. At the same time, the motor control unit logs any reverse actions, which typically happen when the shredder encounters resistance or a clog.

By combining visual data with motor behavior, the system learns to identify waste types that are likely to cause problems. This forms the basis for predictive maintenance.

3.2 Data Collection and Preparation

During regular operation, the camera records video while the shredder processes various waste materials. When the motor reverses, the system marks that moment and extracts the corresponding image frames.

Trained images are labeled manually as either “clog” or “no clog,” based on the motor’s response and the appearance of the waste.

To prepare the data for training, images were gone under a simple process of resizing, lighting and contrast adjustment. Basic image augmentation techniques such as flipping, rotating, and zooming also applied to increase the variety of training samples and improve the model's ability to generalize.

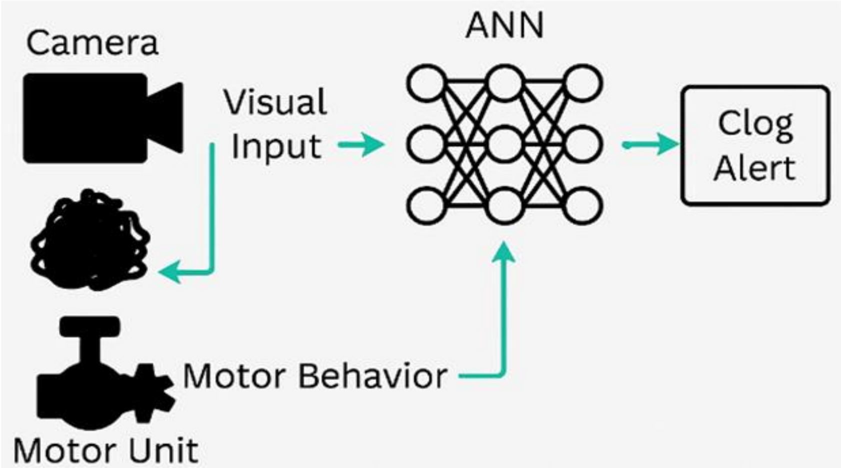

Figure 1: System architecture for real-time clog detection.

3.3 ANN Model Design

In order to evaluate the model's performance mainly Cross-validation is applied. Carefully processing with data labeling and randomization to avoid possible memorization.

Further the evolvability throughout the long span between occurrences is also taken into consideration. This is indeed one of the requirements from plant. The ANN model was designed to adapt to evolving input patterns, with architecture tuned iteratively based on performance metrics such as accuracy, precision, and adaptability. Which is very reasonable that computer architecture and ability of AI evolve rapidly compared to machine itself.

3.4 Real-Time Operation and Integration

Once the model is trained, it is deployed on a local processing unit that connects to both the camera and the motor control system. whenever waste flows just before the shredder, the system analyzes each image in real time. If the model predicts a high chance of clogging, it sends an alert to the operator and logs the event. We can use this AI generated alert in future steps to divert traffic for incoming waste.

This allows operators to take action before a full blockage occurs. Over time, the system builds a record of clog-prone waste types and helps refine maintenance schedules. It is designed not only to detect problems but also to support smarter decision-making and improve the overall efficiency of waste processing

4. EXPERIMENTAL SETUP

To test how well the proposed system works in a real-world setting, we carried out a series of experiments using a working industrial shredder. The aim was to see how accurately the ANN model could identify waste items that tend to cause clogs, and whether it could do so fast enough to be useful during live operations.

4.1 Equipment and Environment

We used a mid-sized industrial shredder that's commonly found in waste treatment facilities. A high-resolution camera was installed above the shredder's inlet to capture video of the waste as it was fed into the machine. This camera was connected to a local processing unit equipped with GPU support, which allowed us to run the ANN model and analyze images in real time.

The shredder's motor control system was designed in such a way that motor runs in opposite direction for a short time to remove the clog. This comes with a built-in alarm for each event. Our aim is to obtain this as a trigger and record the data together with camara data. System is configured to log every reverse movement with a timestamp. These reverse events were used as indicators of clogging and helped us match image data with actual machine behavior.

The system was deployed on a local processing unit with GPU support, enabling real-time image analysis and alert generation. Hardware configurations are modular and subject to upgrade as system requirements evolve.

4.2 Building the Dataset

Over several days of operation, we collected video footage and motor logs while the shredder processed a wide range of waste materials. These included plastic containers, metal scraps, tangled wires, and mixed composite items. When shredder motors reversed, relevant images are trained as "clog" or otherwise "no clog, " causing. For improvement on accuracy and image diversity, further applied simple image transformations like flipping, rotating, and adjusting brightness. Modelling using 400 labeled images, resulting in a split between the two categories.

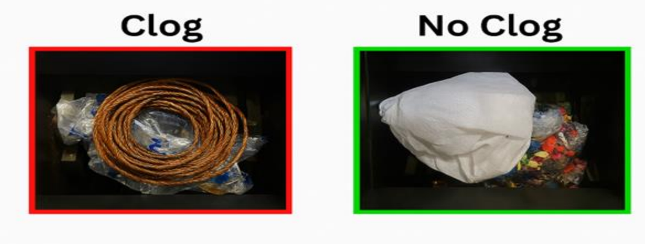

Figure 2. Sample Clog and *No Clog* activations

Figure 2. Sample image frames labeled as 'Clog' and 'No Clog' as result of training.

The left image shows a tightly coiled wire mixed with plastic debris, which triggered a reverse motor event. The right image shows loosely arranged waste, including a crumpled plastic bag and small fragments, which passed through without issue. These examples illustrate the visual features used to train the ANN model.

4.3 Training the Model

Split between training and testing are such that, Objective ANN model was trained using 80 percent of the dataset, rest 20 percent for validation. The model trained over 50 cycles (epochs) with a batch size of 32. Training progress is carefully monitored for accuracy along with loss graphs to ensure its efficiency and accuracy. Cross-validation and randomization also performed for accuracy.

4.4 Live Testing

Once the model was trained, we deployed it on the same processing unit used during data collection. As the shredder ran, the system analyzed each incoming image in real time. If the model predicted a high chance of clogging, it sent an alert and logged the event.

During live testing, the system was able to identify clog-prone waste quickly and accurately. This showed that the approach could be used not just for detection, but also to support smarter maintenance planning and reduce unexpected downtime.

5. RESULTS AND DISCUSSION

After training the ANN model and testing it in both controlled and live conditions, we found that the system performed reliably and offered practical value for real-time clog detection. The results showed that the model could recognize clog-prone waste with a high degree of accuracy and respond quickly enough to support day-to-day operations.

5.1 How the Model Performed

Test results show that trained model reached an overall accuracy of 92%. It consistently identifies clog-prone waste with strong precision despite the limited data proving its ability for determining clog causing waste.

Many false positives came from waste items that looked similar to known clog triggers such as tangled wires or oddly shaped waste. In these cases, it can be considered for the subject to guillotine line instead of shredder. Thus, test results already achieve overall positive results.

Table 1: Performance Metrics of the ANN Model

Metric	**Value**	**Interpretation**
Accuracy	92%	Overall proportion of correct predictions across both *clog and no-clog* cases
Precision	91%	Percentage of predicted clogs that were actual clogs (low false positives)
Recall	90%	Percentage of actual clogs that were correctly identified (low false neggatives)
Inference Time	< 0.5 sec	Time taken to process each image and generate a prediction during live operation
Dataset Size	400 images	Total labeled samples used for training and validation (200 clog, 200 no clog)

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Summary of evaluation results for the supervised ANN model used in real-time clog detection. Metrics reflect model accuracy, responsiveness, and dataset scope.

5.2 Real-Time Detection in Action

When we deployed the model during live shredder operation, it was able to process incoming images in less than half a second. This meant alerts could be sent almost instantly when the system spotted something risky. Operators found the alerts helpful, especially during busy shifts when manual monitoring wasn't always possible.

The system also kept a log of each prediction and matched it with motor behavior. Over time, this created a useful record that helped identify which types of waste were causing the most trouble. This kind of insight is valuable for adjusting intake procedures or planning maintenance more effectively.

5.3 What We Learned

One of the most useful findings was the clear link between certain waste features—like bulkiness, irregular shapes, and tangled textures—and reverse motor events. These patterns can help facilities rethink how they sort or prepare waste before shredding.

The system also proved helpful for maintenance planning. By tracking how often clog predictions occurred and when, operators were able to schedule inspections and blade replacements more strategically. This reduced downtime and helped extend the life of the equipment.

Table 2: Waste Categories Linked to Clogs

Waste Type	Visual Characteristics	Likelihood of
Tangled Wires	Coiled, prone, lengthy, often snakes through gaps and wraps around motor unit components	High
Plastic Bags, Wrappers, Soft Containers	Lightweight, tend to bunch up and expand, reducing ability to flow through gaps	Medium
Cardboard Sheets	Flat, brown, uniform	Low
Mixed Debris	Unsorted, overlapping textures	Medium

Summary of waste types identified as most likely to obstruct the shredder. Visual features illustrate how each type contributes to clog risk.

5.4 Where It Can Improve

While the results were encouraging, there are areas that could be strengthened. The dataset was relatively small and came from a single facility, so expanding it with more waste types and lighting conditions would help the model generalize better.

Also, the current model only gives a yes-or-no answer about clog risk. Future versions could offer more detail, such as the severity of the clog or the type of waste involved. Combining image data with sensor readings might also improve accuracy and make the system even more responsive.

5.5 Limitations

While the system performed well in both validation and live testing, there are a few limitations to consider. The dataset was collected from a single facility, which may limit how well the model generalizes to other environments. Lighting conditions, waste composition, and shredder configurations can vary widely across sites. Additionally, the current model uses binary classification and does not account for the severity or type of clog. Expanding the dataset and incorporating multi-class outputs or additional sensor data could help address these limitations in future versions.

6. CONCLUSION

This study explored a practical method for detecting shredder clogs before they occur, using a supervised artificial neural network trained on visual and motor data. By linking camera footage with motor behavior, especially during reverse movements, the system learns to recognize waste items that are likely to cause interruptions.

The results showed that the model could identify clog-prone materials with high accuracy and respond quickly during live operations. Operators found the alerts useful, and the system's event logs provided helpful insights for planning maintenance and adjusting intake procedures.

What makes this approach effective is its ability to learn from actual plant conditions and apply that knowledge in real time. Rather than sticking to rigid rules or doing manual checks, the system adjusts itself to handle the complexity of industrial waste and helps you make more knowledgeable decisions.

Although the current version focuses on binary classification and was tested in a single facility, it lays the foundation for more advanced applications. Future versions could offer more detailed predictions, work with larger datasets, and combine image data with sensor readings. With continued development, this system could become a reliable tool for improving safety, reducing downtime, and making industrial waste processing more efficient.

This system offers a practical step toward smarter, safer, and more responsive waste management, with clear benefits for operational efficiency and long-term equipment care.

7. FUTURE WORK

While the current system has shown strong potential, there are several ways it could be improved and expanded in future research.

One clear next step is to grow the dataset. Right now, the model has been trained on data from a single facility, which means it may not perform as well in different environments. Collecting more images and motor data from other sites, with a wider mix of waste types and lighting conditions, would help the model become more flexible and reliable.

Another area to explore is the type of output the system provides. At the moment, it gives a simple yes-or-no answer about clog risk. Future versions could offer more detailed predictions, such as the severity of the clog or the specific type of waste involved. This would give operators more context and help them respond more effectively.

There's also room to combine visual data with other sensor inputs, like vibration, torque, or sound. A system that uses multiple types of data could make even more accurate predictions and offer a fuller picture of what's happening inside the shredder.

Finally, it would be useful to connect this system with broader maintenance planning tools. If clog predictions could be linked with maintenance schedules, inventory tracking, and operator feedback, facilities could move toward a more coordinated and data-driven approach to equipment care.

These improvements would not only make the system smarter but also help waste processing facilities run more safely and efficiently

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