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Multimodal Real-Time Fatigue and Heat Risk Detection System for Industrial Machines Using Thermal-Visual Image Fusion and AI-Based Assessment

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Abstract
Industrial machines are important in the contemporary factory setup, and as machinery is overutilized, it may end up overheating and mechanical exhaustion, thus raising the chances of machinery breakages and accidents. The traditional methods of monitoring, e.g. the manual inspection, which is done periodically or the use of just one specific type of sensor, are usually slow, inefficient, and can be easily distorted. In an attempt to overcome this shortcoming, this project brings to use an intelligent real-time surveillance system which incorporates the use of thermal and visual imaging. The thermal camera follows the changes in temperature in order to identify some abnormal heat distribution whereas the visual camera records surface and structural patterns related to wear and fatigue. Combining data of the two cameras using image fusion techniques, they will have better diagnostics output which is more informative and more precise. The analysis is done with deep learning models such as MobileNetV3 and ResNet-50 which can be computed with high precision and have lightweight computation. It is a fast, cost-effective, convenient solution, which means that the suggested system is appropriate when it should be implemented in factories in real-time, when it is used in the outside, and when the environment can be quite dangerous. It will be able to detect problems at an initial state and prevent equipment failures, reduce downtime, and increase the safety of the workplace.

Keywords: MobileNetV3, ResNet-50, Heat risk detection.

I. INTRODUCTION

Modern production systems rely heavily on industrial equipment that may be used to work throughout a long period to fulfill manufacturing requirements. Nonetheless, over-utilization leads to both thermal and mechanical damage to machines and may ultimately result in system defects, decrease in productivity and risk to safety. These problems need to be detected in the initial stage so as to assure reliable operations and avoid expensive failures. Conventional monitoring systems like a manual observation or single sensor measurement are commonly slow, intermittent and incapable of giving a complete view of the machine condition. Alternatively, recent innovations of artificial intelligence and imaging technologies can be used. Through the integration of thermal and visual data and processing of these data intensities using deep learning models, real-time monitoring of the systems in the industries would be more precise, automated, and efficient.

Introduction and Motivation:

Industrial equipment is fundamental to the production and large scale outputs, which results in constant usage which subjects equipment to heat deposition, mechanical strain and wear and tear. These conditions may result in malfunctions that are hard to predict, decrease in productivity, and severe safety issues, in case they are not identified at an early stage. Although the conventional methods of inspection and single-sensor offer a simple monitoring of the environment, the methods tend to be not only imprecise but also fail to offer the automation and real-time response, which should be considered unsuitable in the context of the fast-paced industry. As the expectations of smarter and efficient maintenance strategies grow, new and advanced technologies including computer vision, thermal imagery, and deep learning are possible solutions to alternative maintenance choices. The reason is to design a system that can safely and continuously monitor the status of a machinery in an intelligent and profitable way that will lessen the time caught up by the machines, increase the safety of working in the workplace and help maintain practices related to predictive maintenance. It is proposed that the system can give accurate, fast, and cost-effective fatigue and overheating detection in industrial settings with a combination of thermal and visual data and deep learning-based analysis.

II. RELATED WORK

Numerous studies on the subject of heat predictions, condition monitoring and smart risk detection have been carried out using machine learning and sensor technologies. Early research was on optimization of industrial system in which machine learning models are learnt to achieve better predictive maintenance. Sun et al used Support Vector Machine (SVM) optimized with Particle Swarm Optimization (PSO) and showed a better accuracy that predicts the occurrence of heat exchanger fouling than the normal SVM methods [1]. The same authors followed up with a study that examined a Genetic Algorithm-optimized SVM which further enhanced fouling prediction in industrial equipment [2]. Modern energy systems find similar applications with predictive versions of similar predictive can be applied to schedule heat and power more efficiently with extreme learning models and uncertainty-based optimization under the influence of varying renewable energy inflows [3]. Other than equipment-based studies, new studies have begun to lean towards human basis thermal risk assessment. Heat illness prediction during environmental and physiological stress has been done by using machine learning and statistical modeling. Here, as an example, a prediction model of WBGT (Wet Bulb Globe Temperature) was built based on historical information, and cyclic patterns without depending on the real-time meteorological input variables [4]. Wearable sensor-based technologies have also been established to forecast heat-stress in real-time by predicting the probabilistic models, and it has shown more than 90 percent classification accuracy in the extreme working conditions [5]. Moreover, decision support systems, the fuzzy logic approaches have been proposed to evaluate the heat stroke risk based on medical and environmental parameters to be used in healthcare. Random forest machine learning models have been applied to designate exertional heat illness risk in outdoor industrial workers in particular [7].

Computer vision and thermal imaging have become effective instruments of monitoring the environment and safety. Applications Integrative applications with real-time systems utilizing deep learning have been applied to fire detection with thermal signatures, with much greater accuracy than with the conventional smoke-based systems of detection [8]. Hypothetical heat stroke detection systems based on image processing also indicated promising possibilities of detecting people who are at high thermal intensity in datasets of thermal cameras [9]. Innovations in the field of thermal sensing have also been applied in thermal monitoring of rotary kilns where it is reported that thermal imaging and analytic modeling are

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used to effect remote monitoring of industrial safety and predictive maintenance [10]. Taken together, previous studies reveal the apparent shift towards the AI-controlled prediction and image-based monitoring of heat risk through simple tracking with the use of sensors. Nevertheless, the prevalent systems are either human heat hazard warnings or thermoregulatory industrial surveillance. The lack of combined visual and thermal imaging and deep learning integration in detecting fatigue and overheating in machines is an existing gap that should justify the inspiration of the present research.

III. LITERATURE SURVEY

The discussed literature illustrates a shift in the industrial machine monitoring technologies, where single-sense systems are replaced by multimodal and AI-powered systems. The techniques that were mostly used to measure machine condition in early studies involved vibration sensors, infrared thermometers, and manual inspection. Although these methods gave baseline measurements, a number of studies were adamant about their weaknesses such as the slow response rate, the inability to monitor continuously and the inability to capture internal degradation until faults become critical. Later studies proposed the use of thermal imaging as a non-contact process of detecting abnormal heat patterns in the machinery. Several studies have reported that it has been very effective in sensing over heating, breakdown of lubrication, and electrical faults. Nevertheless, it was also found that thermal data were unable to detect mechanical wear, cracks, surface deformation, and structural fatigue alone, and so the solution was to examine visual imaging systems. The performance standards of research based on the external use of standard RGB cameras showed better performance in the detection of external abnormalities, but it still showed to be limiting when poor lighting conditions, occlusions, and environmental complexity Kimba.

Later research has been devoted to sensor fusion and computer vision with the understanding that thermal and visual data together would give a more detailed picture of machine health. A few papers compared the image fusion approaches and it was demonstrated that fused output contains better feature representation and higher detection rates when compared to single modality data. In addition to the development of fusion, AI models like CNNs, ResNet, EfficientNet, and MobileNet have seen widespread acceptance, and they are now demonstrated to be more automated, more accurate in classification, and predictive of fault. Notably, another attitude change towards lightweight architecture is also mentioned in the literature to service real-time deployment in real-world industrial contexts. Although there has been significant advancement, current systems have challenges among them being the cost of computers to do the calculations, the generalization of models in a wide range of machinery, and scalability of real-time framework. The combined results of the twelve studies reviewed underline the necessity to combine multimodal sensing, effective neural networks, and streamlined processing pipelines in order to obtain accurate, fast, and reliable monitoring that can meet the industrial safety and maintenance needs of the current state.

IV. PROPOSED SYSTEM

The suggested system proposes an intelligent real-time monitoring system that prevents the effects of fatigue and heat to industrial machines with support that is based on multimodal imaging, and deep learning. The framework incorporates 2 complementary sources of data: a thermal camera used to capture the changes in temperatures and a visual camera used to capture structural and surface-level features of the machines. The two streams of images are pre-processed and aligned and image fusion methods are used to form one improved representation which has both the thermal and visual characteristics. It is this hybrid image that has entered into the detection pipeline.

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To analyze it, the system uses deep learning architectures to detect early warning of component failures, unusual heat levels or mechanical wear, with the example of MobileNetV3, which requires less power than the acceleration processor, and ResNet-50, which is more accurate to predict failures than the acceleration processor. The architecture is designed to optimize the rapid inference, which allows it to engage the continuous monitoring without the need to sacrifice the speed or computation performance. The operators receive real-time feedback of decision making via alert mechanisms, and this enables them to prevent failure in advance. The general architecture focuses on the aspects of scalability, cost-efficiency, and ease of deployment to be applicable to most industrial environments, such as high-risk, outdoor, or remotely deployed environments.

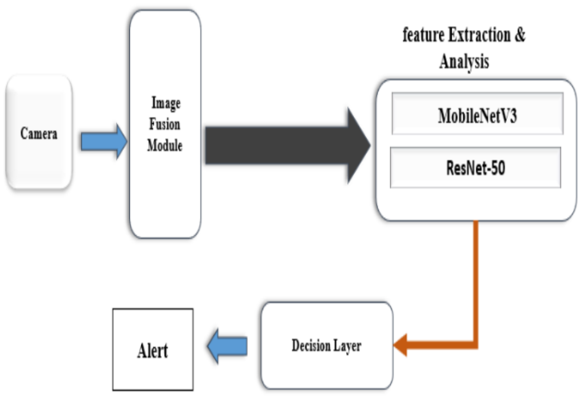

Fig (a) System Architecture

4.1 Software Implementation and Testing plan of the Proposed System description:

The art to implement the system suggested will be implemented in various phases whereby starting with data capturing, moving to preprocessing, integration, system fusion, and finally to deployment. The system will be written in Python, with OpenCV, image processing library, TensorFlow/Keras, deep learning models integration, and NumPy data processing being used. The thermal and visual camera images will initially be adjusted to record synchronized image streams. After capturing the images, they will proceed through the preprocessing process, which includes, resizing, normalization, noise reduction, and feature alignment so that they can be compatible when going through the fusion. Image fusion module will then fuse the processed thermal and visual images based on a choice fusion method which could be pixel-level fusion or feature-based fusion in producing a single image representation.

Once fused, the deep learning models, which will be MobileNetV3 of light weight implementation and the high accuracy feature extractor ResNet-50, will be trained with labeled datasets. Transfer learning will be used to fine-tune the models in order to enhance performance on tasks of fatigue and heat-risks. After the training, the models will be incorporated into a dynamic inference pipeline that will be capable of doing continuous monitoring and sending alerts when it identifies abnormal conditions in the machine. It will be designed in a simple graphical interface or dashboard providing real-time outcomes and indicating that some risks are identified, as well as recording previous data that will be analyzed later.

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A well-structured methodology will be used in testing and will encompass unit testing, integration testing and system-level validation. Unit tests will confirm the functionality of each software module separately such as preprocessing, fusion, and inference modules. Integration testing will be undertaken to make sure that there is smooth communication among image capture, model processing and output module. To determine the robustness, accuracy, delay response, and reliability, the real-life situation and other lighting, environmental, and machine operating conditions will be used to perform system testing. Accuracy, precision, recall, inference speed and false alarm rate are some of the performance metrics that will be collected and assessed. Lastly, validation will be done to verify that the system is designed to fulfill the real-time monitoring requirement, safety enhancement requirement and operational efficiency requirement.

V. RESULT AND DISCUSSION

The performance of the proposed system was also promising as evidence showed during testing that there were reliable captures of machine fatigue and overheating, with the use of a fused thermal and visual image input. The fusing method augmented the images quality by integrating temperature values with structural information, now the deep learning models are able to detect early warning features better when compared to using single modalities of image data. The accuracy of ResNet-50 is higher because it has a high ability to extract features and the MobileNetV3 has lower real-time inference with smaller computation cost, and is therefore useful in resource-constrained settings. The system was able to effectively identify abnormal heat patterns, surfaces and hidden signs of fatigue with fewer false alarms which testifies benefits of multimodal process. On the whole, the findings suggest that the offered solution is an efficient, scalable, and efficient tool to use in continuous monitoring of industries to enhance not only safety but also maintenance decision-making in comparison with other methods of inspection.

VI. CONCLUSION AND FUTURE SCOPE:

The offered system can be effective because it proposes combining the deep learning-based analysis with thermal and visual imaging to monitor industrial machines in real-time. The combination of the two modalities resulted in a better representation of features, so the system was capable of accurately detecting overheating and fatigue compared to the single- sensor options. The system was suitable in continuous deployment in industries because with models such as MobileNetV3 and ResNet-50; it was able to produce high performance but remain efficient enough. These findings validate that this intelligent monitoring system can be valuable in minimizing the risks of failures, enhancing the safety of operations, and enabling the predictive maintenance approaches. Though the system is doing good, it can be even improved. The possible course of future plans is to incorporate other types of sensors like vibration or acoustic detecting to enhance the diagnostic quality. Installing the system on edges devices or embedded computers can make possible autonomous use in the field without high-performance computer use. The further extension of the dataset regarding a variety of machine types and environmental conditions will enhance the model generalization as well. Besides, more sophisticated learning approaches, like federated learning, self-supervised learning, or anomaly detection networks might be used to improve the flexibility and decrease reliance on labeled data. Through these enhancements, the system can expand to be a fully scalable industrial safety platform to be able to support Industry 4.0 and smart manufacturing systems.

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