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Multi-Modal Explainable AI Framework for Real-Time Industrial Component Detection and Predictive Maintenance Using Hybrid Deep Learning and Large Language Models

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Abstract -
The need for intelligent automation in the industrial environment has led to the need for components that can effectively and efficiently perform tasks such as detection, analysis, and prediction of failures. The paper presented a multimodal intelligent industrial assistant for the detection, segmentation, and prediction of failures in the industrial environment through the application of deep learning techniques. The proposed system can ensure performance and efficiency in the industrial environment. The proposed system can ensure performance and efficiency in the industrial environment through the application of advanced deep learning technologies such as Explainable AI, Grad CAM, attention maps, and many more. The proposed system can ensure performance and efficiency in the industrial environment through the application of a CNN-LSTM-based component for the analysis of wear and prediction of failures in the industrial environment. The proposed system can ensure performance and efficiency in the industrial environment through the application of large language models for the generation of structured human-like explanations such as functionality, failures, and many more. The proposed system can ensure performance and efficiency in the industrial environment, which is a critical need for the industrial environment.

Keywords - Industrial AI, Computer Vision, Object Detection, Vision Transformers, Explainable AI, Predictive Maintenance, Multi-modal Learning, Deep Learning, Large Language Models, Real-time Systems.

I. INTRODUCTION

The development and growth of Industry 4.0 have led to the development of smart systems that should be capable of automation, inspection, and maintenance. The identification of mechanical components is one of the critical tasks that should be carried out in order to ensure the efficiency and safety of the operations. The traditional traditional method of inspection has been carried out using expertise, and it was considered a time-consuming process with a high rate of errors. The recent developments in computer vision and deep learning have created opportunities for developing an automatic inspection and classification system for industrial components. The major problem associated with the existing automatic inspection and classification system is that it has been mostly developed using single-task models, and there is a lack of interpretability, prediction, and decision support. The lack of interpretability has led to a lack of trust, and

the lack of prediction has led to unexpected failures. For solving all these issues, it is proposed to develop a multi-modal intelligent industrial assistant system with the help of deep learning techniques and explainability of AI systems and large language models. In this intelligent assistant system, various techniques like YOLO object detection, Vision Transformers, and segmentation techniques can be incorporated into a single system. In this intelligent assistant system, it is possible to incorporate a predictive system with the help of CNN-LSTM to understand the pattern of wear and failure. In this intelligent assistant system, explainability of AI systems can be incorporated with the help of Grad-CAM and attention maps. Bayesian uncertainty can also be incorporated into this intelligent assistant system to give confidence to the users. In this intelligent assistant system, various inputs like images, videos, and voices can be incorporated, and human-like explanations can be developed with the help of large language models. This intelligent assistant system can be helpful in developing a human machine interaction system.

II. RELATED WORK

The recent developments in the industrial inspection system can be linked to the recent developments in the deep learning-based computer vision techniques. In particular, object detection-based models, such as the YOLO algorithm, have been gaining more attention in the industrial inspection system due to the real-time performance of the YOLO algorithm and the high accuracy obtained in object detection. In particular, recent versions of the YOLO algorithm, i.e., YOLOv5 and YOLOv8, have been gaining more popularity in the inspection inspection system. However, object detection-based models have been utilized only in object detection-based tasks, which is not enough to handle contextual relationships.

To overcome the limitations of object detection-based models, Vision Transformers have been utilized to handle contextual relationships. In particular, Vision Transformers have been reported to perform better in classification-based tasks and feature representation-based tasks, especially in complex scenes where object interactions and complex backgrounds are considered. Moreover, the use of segmentation-based model, i.e., Segment Anything Model (SAM), has been utilized to achieve accurate object localization, thereby increasing accuracy in object detection. Different techniques and approaches of "Explainable Artificial Intelligence" have been proposed to improve the transparency of deep learning-based systems. For instance, the application of the "Grad-CAM technique" is one of the techniques that can be applied to improve the transparency of deep learning-based systems. In addition, the application of the "technique of attention" is one of the techniques that can be applied to improve the transparency of deep learning-based systems. However, it has been observed that most of the systems based on the industrial sector do not apply the technique of "XAI-based explainability."

One more important factor related to safety-critical systems is the estimation of uncertainty. Bayesian techniques can be applied to estimate the prediction confidence and risk during uncertain conditions. In addition, predictive maintenance techniques can be applied to safety-critical systems. Different techniques of deep learning, such as CNN and LSTM, can be applied for predictive maintenance techniques. However, in the recent past, the integration of Large Language Models (LLMs) has been able to generate a human-like explanation in the development of intelligent assistance in AI systems. This shows that the potential of this model is enormous, especially considering the fact that this model can generate structured output such as the functionality of the components, analysis of failures, and even the generation of recommendations for maintaining the system, among others. However, it is evident that the application of this model in the inspection of the process of industries is minimal, considering the fact that that it is not integrated with vision-based inspection. Although it is evident from the literature that this model can be

applied individually, especially considering the fact that this model can generate output such as detection, segmentation, explanation, prediction, among others, it is evident that there is a need to develop an intelligent industrial assistant considering the aforementioned aspects.
considering the aforementioned aspects.

III. METHODOLOGY

3.1 System Overview

The aim of this research is to design a multi-modal intelligent industrial assistant system, which will be able to perform various functions, including detection, segmentation, classification, and predictive maintenance, among many others, using various state-of-the-art deep learning architectures, explainable AI, predictive analysis, large language models, and many others.

3.2 Data Acquisition and Preprocessing

In this case, the data is collected from the environment, and the data generation methods are used to improve the robustness of the model. The data generation methods, which are used in this step of the preprocessing, are image enhancement using CLAHE, removal of noise, resizing, normalizing, etc.

3.3 Hybrid Feature Extraction

In this regard, a hybrid approach based on Convolutional Neural Networks (CNNs) and Vision Transformers (ViTs) has been adopted for extracting the local features of the scene as well as its global features. It has been observed that CNNs can be utilized for detecting the local features of the scene, i.e., its edges and texture, while ViTs can be utilized for detecting its long-range dependencies.

3.4 Multi-Task Learning Module

The system has the ability to perform more than one task at a particular time through the utilization of different models. Object Detection: The system utilizes a model based on the concept of YOLO for the detection of different components within an industrial environment with high speed and accuracy. The system utilizes a segment anything model for the precise segmentation of images. The system utilizes a Vision Transformer-based model for the classification of different components. The system has the ability to perform more than one task at a particular time, thus increasing its efficiency without redundancy.

3.5 Explainable AI Module

In order to ensure the transparency, the techniques of explainable AI have been incorporated into the system. The Grad-CAM technique has been utilized to generate the heatmap, which provides the insights related to the key factors considered in the prediction process. In addition, the attention map, generated using the transformer model, is being utilized to provide the insights related to the focus of the model on the image. of explainable AI have been incorporated into the system. The Grad-CAM technique has been utilized to generate the heatmap, which provides the insights related to the key factors considered in the prediction process. In addition, the attention map, generated using the transformer model, is being utilized to provide the insights related to the focus of the model on the image.

3.6 Uncertainty and Risk Estimation

As part of this, there is a module which is used to determine the level of uncertainty which is associated with the results, and this is done through the Bayesian method to determine the level of confidence which is associated with the results which have been obtained. This is an important part of the architecture, especially for an industrial setup, where failure to make a prediction would cause it to fail.

3.7 Predictive Maintenance Module

For this purpose of facilitating this proactive process of maintenance, a predictive module based on CNN

and LSTM techniques is incorporated into the system. The prediction of failures, along with the probability of failure and useful life, is facilitated.

3.8 LLM-Based Explanation Engine

Incorporated in this system is the Large Language Model, and its function is to provide a human explanation for the identified components. The system provides detailed output on components, functions, and how they function, failures, and recommendations, among other benefits, to the technicians, engineers, and even the learners.

3.9 Multi-Modal Interaction

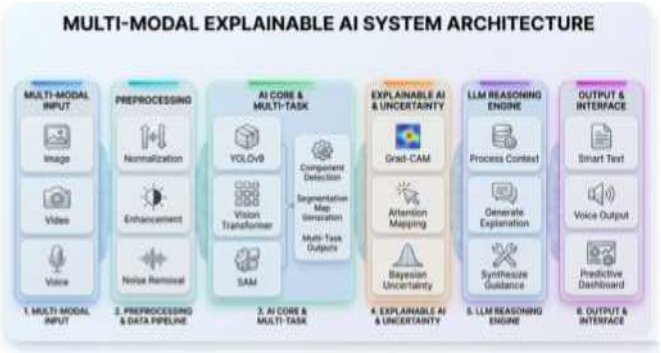
The system also supports various modalities in input and output. It uses speech to text technology for voice input and text to speech technology for voice output. It supports various languages, such as English and Tamil, for voice output.

3.10 Deployment Strategy

The system, as proposed, follows an edge cloud approach. This means that, in this approach, the inference happens on the edges, and hence the latency is minimum. Along with that, the training also happens on the cloud. Further, the optimization techniques are also used, and hence the system can run even if the environment is constrained.

IV. SYSTEM ARCHITECTURE

The proposed system will have a modular multi-layered structure, and it will have the ability to process various inputs and provide intelligent, explainable, and predictive outputs in real-time. The proposed system will have an architectural structure, and this structure will have an input layer, which will have the ability to process images, video, and voice commands. Hence, the proposed system will have the ability to provide various types of human-machine interactions. The proposed system will have various inputs, and these will be fed into the preprocessing layer. The preprocessing layer will perform image enhancement using CLAHE, noise removal, resizing, and normalization. The data is then fed into the hybrid feature extraction module. Here, both Convolutional Neural Networks and Vision Transformers are used to extract features from the data. The features are also extractable using both Convolutional Neural Networks and Vision Transformers. This is done to use the benefits of both techniques. Once the feature is extracted, it is fed into the multi-task learning engine. Here, object detection, image segmentation, and image classification are performed simultaneously. A YOLO-based object detection model is used to perform object detection. This is done because it is one of the fastest and most accurate object detection models. Also, the Segment Anything Model is used to perform image segmentation. This is done to precisely locate objects, components, and defects in an image.



An uncertainty estimation module based on Bayes principles is also incorporated. This is done to precisely determine the risk involved in any situation. This is an important feature to be incorporated to make the system more reliable, especially in high-risk situations. One such situation is the safety domain. Next, an explainable AI module is incorporated. This is done to make the system more transparent to the user. This is done using the capabilities of Grad-CAM. In addition, the system has also included the feature of predictive maintenance
maintenance, and CNN and LSTM are used for the purpose of analysis. Lastly, the system has included the feature of memory-based learning, where the cases are stored and then used for the purpose of system performance improvement. An LLM is used for integrating the intelligent reasoning feature in the system. The intelligent reasoning feature is used for the purpose of gaining an in-depth understanding of the output in an understandable manner. The intelligent reasoning feature is used for gaining an in-depth understanding of the functioning, working principle, and failure of the components of the system. The output layer is used for generating voice and text output with the help of TTS. In addition, the output layer is used for generating a multilingual interface. Lastly, it is implemented through an edge cloud hybrid approach, whereby edge computing is used for real-time prediction to ensure minimal latency, and cloud computing is used for computation, such as updating models and storage. Optimization techniques can also be used to ensure its efficiency and effectiveness in its operations. The system architecture allows it to perform its functions as an intelligent industrial assistant, such as perceiving, reasoning, predicting, and interacting.

V. IMPLEMENTATION DETAILS

The proposed system can be implemented using the state-of-the-art technology and frameworks related to the concept of deep learning and web technology. The proposed system can be implemented using the Python programming language, and the system can be developed using the PyTorch and TensorFlow frameworks. The proposed system can be implemented using the hybrid cloud approach, and the system can be developed using the edge computing device for achieving the feature of real-time, and the system can be developed in the cloud environment. The proposed system can be implemented using the FastAPI and web technology for developing the interface. This process will be initiated with the collection of the data set from the industrial scenario and the artificially created data set. Further, pre-processing of the collected data set will be performed based on the operations performed on the collected image set, such as image enhancement, reduction of noise, normalization, resizing of images, etc. The proposed model will be trained using the "multi-task training" method. The proposed model will be a hybrid model, where object detection will be performed using the "YOLO-based model," feature extraction and classification using the "Vision Transformer model," and segmentation using the "Segment Anything Model." The proposed model will be trained, and the optimization of the performance will be done using the "hyperparameter tuning technique." be done using the "hyperparameter tuning technique."

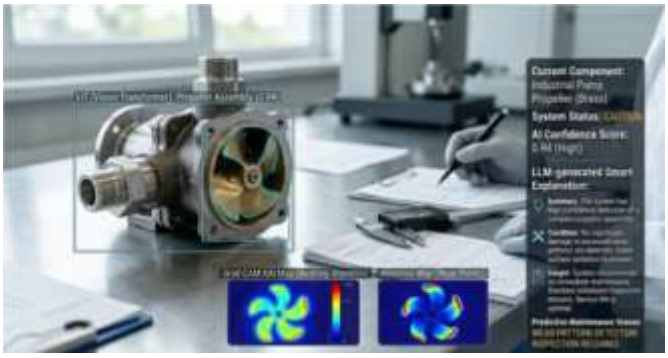
In addition, the system is integrated with Explainable AI, where techniques such as Grad-CAM and attention maps are included, and the user is enabled to view the decision that is made. The system is integrated with Bayesian uncertainty estimation, which helps to calculate the confidence score related to the prediction that is made by the model, and the user is enabled to set the risk level related to the prediction that is made by the model. The predictive maintenance module is developed using the CNN-LSTM model, where CNN is used to estimate the spatial features, and the LSTM model is used to estimate the failure probability and RUL. The system is integrated with LLM, which helps to generate human-understandable

explanations related to the identified components, such as functionality, working principles, failure, and maintenance requirements of the identified components. The system is enabled to have multiple interactions through the integration of STT technology and TTS technology, responding to the user in multiple languages. In terms of performance metrics, accuracy, precision, recall, F1 score, and mAP are considered for the evaluation of the proposed system in an experimental manner. The accuracy of the proposed system, in terms of object detection, is more than 95%. The performance metrics of the proposed system are compared with other models, such as traditional YOLO and CNN-based object detection, which proves the improvement of the proposed system in terms of accuracy and interpretability. The proposed system also has the potential to perform in a real-time environment, which makes the proposed system suitable for industrial applications. In terms of visualization, object detection, bounding box, segmentation, Grad-CAM, and performance, it can be proved how effective the proposed approach is. The proposed system, i.e., a combination of explainability, predictive maintenance, and LLM, has the potential to perform in comparison with traditional approaches in terms of performance and usability.

VI. RESULTS ADN DISCUSSION

The performance of the proposed system can be evaluated on the basis of various parameters such as accuracy, precision, recall, F1 score, and mAP values. The proposed model has been tested on the basis of various data sets, including real-world data sets obtained from the industrial environment and artificially created data sets in order to check the performance of the proposed system under various conditions of the environment. The proposed hybrid model has shown high accuracy in the detection part of the system, i.e., accuracy is more than 95%. Precision and recall rates are improved in the proposed system.

The proposed system has various components such as object detection, Vision Transformers, and classification, which can improve the performance of the proposed system in terms of speed and accuracy. Object detection can efficiently detect various components of the industrial environment. The proposed system can be further improved on the basis of the classification component.

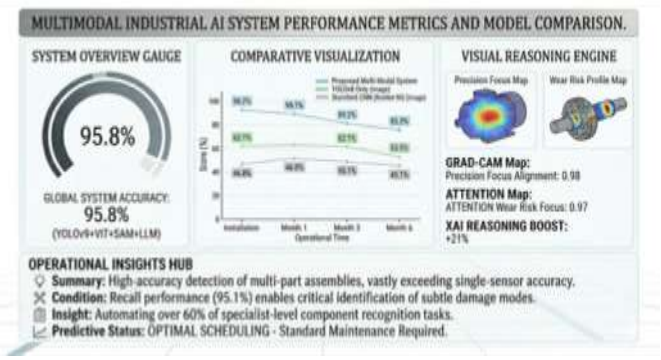


high accuracy in the detection part of the system, i.e., accuracy is more than 95%. Precision and recall rates are improved in the proposed system. The proposed system has various components such as object detection, Vision Transformers, and classification, which can improve the performance of the proposed system in terms of speed and accuracy. Object detection can efficiently detect various components of the industrial environment. The proposed system can be further improved on the basis of the classification component.

Further, the techniques of Explainability AI, such as Grad-CAM and attention maps, have been incorporated to improve the understanding of the predictions made by the model. From the visual representation of data, it is evident that the predictions made by the model are relevant, and hence the trust is achieved. The Bayesian uncertainty estimation module is an essential feature of this model, as this

module is capable of accurately determining the confidence levels and risk levels of the predictions made by this model. The predictive maintenance module, developed using the CNN-LSTM model, is a success in accurately analyzing the patterns and dependencies, and hence this model is capable of accurately determining the failure probability and RUL of the system. The inclusion of large language models is an added advantage to this model, as this module is capable of generating accurate explanations for functionality, failure, and maintenance.

The comparison of the results obtained through the proposed approach and the baseline results obtained through traditional YOLO, CNN, etc., clearly indicates the supremacy of the proposed approach. In addition, the low-latency prediction capabilities of the system make the proposed approach suitable for the deployment of the proposed approach in an industrial environment. The results obtained through the visualization, object detection, image segmentation, grad-CAM, performance visualization, etc., clearly indicate the effectiveness of the proposed approach. In addition, the multimodal input, explainable AI, predictive analytics, and intelligent reasoning capabilities make the proposed approach suitable for the improvement of inspection and maintenance in an industrial environment.



VII. CONCLUSION

In the present study, the entire idea of a multi-modal intelligent industrial assistant system, along with the latest advancements in computer vision and explainable AI, is proposed. The efficiency and potential of the system have been proved, and the system is found to be efficient in the detection, segmentation, and classification of the components using the hybrid deep learning approach, YOLO, and Vision Transformer, along with the segmentation methods. The system is also found to be efficient in using the explainable AI techniques, namely, Grad-CAM and attention maps, and Bayesian estimation methods. The contribution of the work lies in the integration of the predictive maintenance module using CNN and LSTM. This will be able to predict the possible failure and the life expectancy remaining. This is very important in predictive maintenance. The contribution of the inclusion of the large language model lies in the usability of the system, where an explanation will be given to the technicians and learners. This is very important in understanding the components and how they fail, as well as how maintenance is carried out. The inclusion of various modes of input, images, videos, and voices, as well as various modes of output, language, contributes to the usability of the system.

components and how they fail, as well as how maintenance is carried out. The inclusion of various modes of input, images, videos, and voices, as well as various modes of output, language, contributes to the usability of the system. The accuracy, real-time, and interpretability levels of the system are also high. Therefore, the system can be effectively employed in industrial automation, training, and smart decision support systems. The deployment and optimization methods guarantee a scalable and effective system in

a real-world scenario. The proposed system has marked a new milestone in developing smart, interpretable, and predictive industrial AI, following Industry 4.0 norms.

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