Intelligent Rocket Condition Monitoring and Fault Detection using Deep Learning

J Jagadeesan, Hardik Agrawal, Aditya Iyer, Vishal Deo Mahto, Harshit Soni

Abstract: Machines, including rockets can develop fatigue over a specific course of time, due to being subjected to constant pressure, and physical functioning. This can cause heat to be built up in certain parts of the machine, or rocket. This puddled up heat can cause leakage in energy, and may result in the loss of energy, due to heat dissipation. The motive of the article is to monitor the health of a rocket. In this, we investigate how the new age technology of deep learning can be applied to images, more specifically, infrared thermal images, to automatically check and to accurately determine the condition of a rocket/machine. We use two cases, i.e. machine fault detection and oil/coolant level prediction, and show that the proposed system is able to detect numerous conditions in normal machines, and even in rockets, very accurately without requiring any detailed knowledge about its general physics, or its functionality, or structure, by taking thermal images as the general input, and taking the excessive heating issues in the rocket engines into consideration. This system incorporates CNN, machine learning, and to a certain extent, deep learning for producing necessary results.

Index Terms: Thermal Images, Rocket, CNN, Neural Network, Deep Learning.

I. INTRODUCTION

The system consists of taking infrared thermal images as input, which is fed to the CNN (Convolutional Neural Network) neural network, and using deep learning, and incorporating machine learning, the necessary predictions and analytical calculations are done. The system uses multiple hidden layers to find out and monitor the health of the rocket/space shuttle, by observing, and noting the color gradients within the infrared thermal images of the rocket, and creating suitable prediction analysis, and algorithms for the expected result.

The goal of the proposed system here is to monitor the overall health of the rocket, and this is done by monitoring both the coolant levels, and the heat levels within the body, and engine of the space shuttle, or rocket. From these measurements, informative characteristics (features) are extracted and interpreted to determine the rockets condition. This sort of falls under the category of Condition Monitoring (CM). Condition Monitoring of a machine and its components is crucial to avoid downtime and unnecessary costs.

II. LITERATURE SURVEY

This section is to discuss about the different methodologies and motivation outcomes from the given references.

1) ”Numerical Simulation of heat transfer performance of an air cooled steam condenser in a thermal power plant”, Xiufeng, Chengwei, Jinjia (Issue 2009) [1]

In this paper, the simulation of the thermal-ow characteristics and heat transfer performance, mainly the numerical simulation, is mainly discussed. It is made of an air-cooled steam condenser in a thermal power plant, and various other factors are also considered, such as the various effects of the ambient wind speed and its direction, height of the air-cooled platform, the location of the main factory building, and condition of the terrain. A simplied physical model of this air-cooled steam condenser is used in the simulation. The effects of the speed of the wind on the heat transfer performance and the corresponding steam turbine back pressure for the different heights of the air-cooled platform are obtained.

2) ”Self-adaptive Fault Diagnosis of Roller Bearings using Infrared Thermal Images”, Zhiqiang, Yu, Richard, Lei (Issue 2017) [2]

This paper mainly discusses the fault diagnosis of the roller bearings in rotating machinery. This detection of fault is of great signicance and importance, as it is mainly used to identify the abnormalities and failures in industrial plants, and machineries. This system incorporates the use of InfraRed Thermal Images for the detection of faults.

3) ”Thermal Image based fault diagnosis for rotating machinery”, Olivier, Raiko, Viktor, Rik, Kurt, Mia, Sofie (Issue 2015) [3]

This paper discusses the importance of Infrared images. Infrared thermal images are crucial for condition monitoring. The thermographic patterns will differ, depending on the fault, or condition of the machine. As of now, only a handful of machine faults have been studied using thermal imaging. Therefore, this paper proposes a convenient and basic system for detecting faults automatically, using infrared images. The images are mainly focused on the bearings of the rotating machinery. This system provides a relatively high rate of prediction accuracy.

4) ”Towards Intelligent Lubrication Control: Infrared Thermal Imaging for Oil Level Prediction in Bearings”, Olivier, Mathieu, Steven, Mia, Rik, Sofie (Issue 2016) [4]

In this paper, the health of the system using lubrication control is discussed, and mentioned in detail. The rolling element bearings can, if left unattended, suffer from losses in energy. This particular problem can be minimized, or controlled, by actively regulating the oil level in the bearings. The oil level has to be kept in check throughout the implementation process. In this paper, infrared thermal images are used for determining for this very purpose of health and fault detection, along with the lubrication/oil levels.

5) ”Deep Learning For Infrared Thermal Image Based Machine Health Monitoring”, Olivier, Mia, Rik, Sofie (Issue 2018) [5]

This paper discusses in detail about the monitoring of a particular machine, whether it be home appliances, or industrial-based machineries. This system incorporates the use of thermal images as input, in order to determine the oil levels, and constantly monitor the health of the machine using this particular input. Using Deep Learning,

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the images are then used to calculate/predict the health of the machine, by using the colour gradients as raw data.

III. SYSTEM OVERVIEW

This system consists of various layers of processing. There are three main layers incorporated into this system, namely Data Annotation, Neural Network (Mainly CNN), and the Output Section. In the Data Annotation part/section, the raw input is given in the format of images, where these images are mainly infrared thermal images. Each of these images have a specific time stamp, and are collected at various instances of the rocket's launch, and pre-launch stages.

The Neural Network part, which mainly utilizes CNN, i.e. Convolutional Neural Network, which is known for its multi- layer perceptrons, which are designed to require minimal pre- processing. CNN, or any neural network in general, works similar to that of the connectivity pattern between neurons within the brain of an animal, or a human being. Therefore, it is mainly inspired by biological processes. CNN consists of input layer, output layer, and multiple hidden layers. Each neuron in a neural network computes a particular or unique output value, by the application of functions to the input values, which are infrared thermal images. In output section, it is checked whether the output obtained is the desired output or not. The model is trained to obtain a suitable data set, in order to increase the rate of accuracy of the desired output.

A. Collection of Thermal Images

In this module, the huge data sets of different types of thermal images of the internal parts of the rocket are collected accordingly. The data sets are then combined to make a single large data set unit to train in the CNN model.

B. Training of The Data Set

In this module, the generated data sets are used to train the CNN model with the given parameters and decided layers.

C. Extracting Features

In this module, areas of high temperature zones that are marked with more darker shades are differentiated from the areas of low temperature zones. Leakages are detected using the low temperature zones.

D. Deployment of The CNN Algorithm

This module allows for the created data sets to be trained in the CNN algorithm, and these trained data sets go through multiple hidden layers. For going through these multiple layers, the images are converted to pixel arrays, i.e. np-array. In each layers, there are formulae that are executed with different parameters to separate out different features with their respective probabilities.

E. Visualization Module

In this module, comparative study of oil and coolant levels and defect graphs are done with the previous available data. Different graphs are created using different tools.

F. Prediction Module

In this module, predictions of oil level, coolant levels, and defects are made using the probabilities from the CNN model.

G. System Design

System design and architecture involves the high level structure of system design, with architectural style and quality attributes. An architectural system design must conform to the major functionality and performance requirements of the system, as well as satisfy the non-functional requirements such as reliability, scalability, portability, and availability. An architecture must describe its group of components, their connections, interactions among them and deployment congu- ration of all components. The diagram should also be simple enough to be understood easily, and effectively, and not cause any sort of misunderstanding of the representation of it, or cause any complications regarding its structure, definition, and the way it is presented.

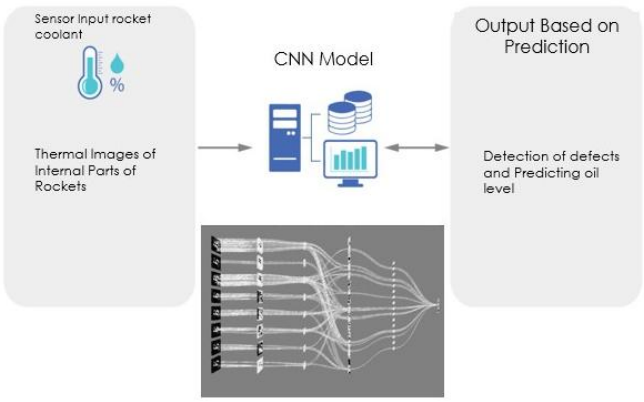

Fig. 1. System Architecture

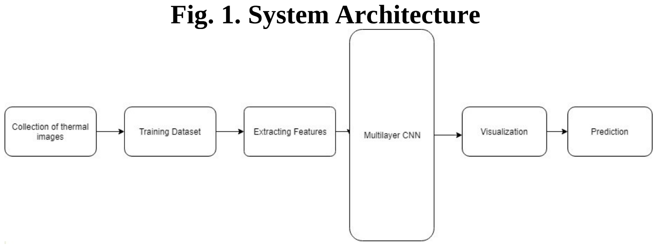

Fig. 2. Data Flow Diagram

IV. PROPOSED SYSTEM

A. Contribution

The goal of the proposed system is to handle the difficulty in determining the health of the Rocket, or Space Shuttle, by carefully examining the colour gradients, as seen due to the varying heat signatures throughout the body of the rocket, and its external framework. The whole process consists of three main sections, or steps, namely Preprocessing, Extraction of features, and Deep Learning, which incorporates the neural network.

In order to overcome any problems that occur during the initial stages, thermal images of different time stamps, i.e., infrared thermal images of different instances of the rocket, that is, before, during, and after lift off, are taken as input, for different preprocessing parameters. These different images of different instances will allow for more accurate calculations and predictions of the output, which may as well be the desired output for the monitoring of the rocket health. The images are analyzed by the neural network for the colour gradients, which are the basic representations of the various heat signatures emitted by the various parts and locations of the

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rocket's internal and external structure and body.

B. Preprocessing

One of the main methods within the proposed system is the preprocessing section. It incorporates the use of a technique called Thresholding. Thresholding is the simplest method of segmentation of an image. This particular method can be used to create binary images from a grayscale image. This means that it can be divided into black and white colours.

1) The Otsu Method

Named after Nobuyuki Otsu, it is one of the simplest and most popular techniques for statistical image thresholding. Otsus rule for selecting the optimal threshold can be written as:

$$T = \underset{t\in[0,L-1]}{\arg\min}\left\{\omega_b(t)\,\sigma_b^2(t) + \omega_o(t)\,\sigma_o^2(t)\right\}$$

where Wb(t) and Wo(t) are the cumulative probability of two classes, i.e., background pixels B(t) and object pixels O(t), and can be defined as:

$$\omega_b(t) = \sum_{i\in[0,t]} h(i),$$

And, the standard deviation of these classes, represented as:

$$\omega_o(t) = \sum_{i\in(t,L-1]} h(i),$$

$$\sigma_b^2(t) = \frac{\sum_{i\in[0,t]}(i-\mu_b(t))^2 h(i)}{\omega_b(t)};$$

$$\sigma_o^2(t) = \frac{\sum_{i\in(t,L-1]}(i-\mu_o(t))^2 h(i)}{\omega_o(t)},$$

In addition, the means of these classes are represented as:

$$\mu_b(t) = \frac{\sum_{i\in[0,t]} ih(i)}{\omega_b(t)},$$

$$\mu_o(t) = \frac{\sum_{i\in(t,L-1]} ih(i)}{\omega_o(t)}.$$

To provide a solid example of segmentation masks obtained by this method, here's an image for represen- tation:

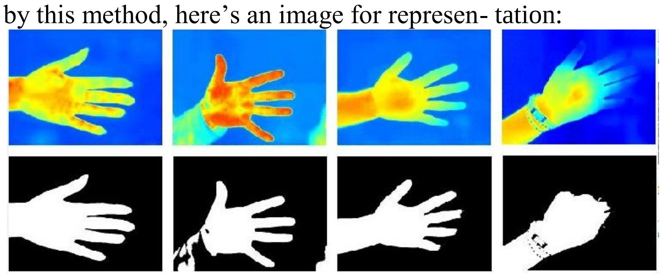

Fig. 3. Input Thermal Image vs Otsu Method Segmentation Masks

To show the segmentation of classes, i.e., colour gradients, which represent the various temperatures, using Otsu's Method, here's an image:

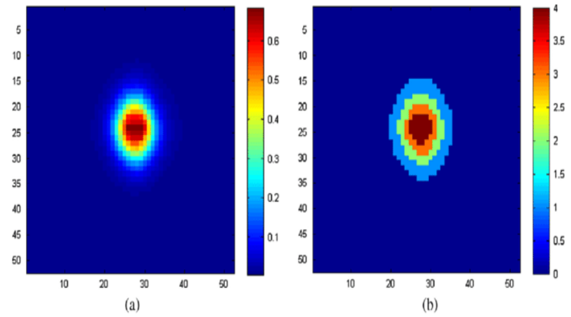

Fig. 4. Segmentation of classes using Otsu Method

2) The Xue Method

In order to further improve the Otsu Method, The Xue Method was proposed. This method uses a median-based extension for the Otsu Method, aimed at improving the robustness of the Otsu Method, with the presence of skew or heavy-tailed class-conditional distributions. Xues rule can be stated as:

$$T = \underset{t\in[0,L-1]}{\arg\min}\left\{\omega_b M_b(t) + \omega_o M_o(t)\right\},$$

Where Mb(t) and Mo(t) represent the mean absolute deviations from the median, and are defined as:

$$M_b(t) = \frac{\sum_{i\in[0,t]} h(i)\left|i - m_b(t)\right|}{\omega_b(t)},$$

$$M_o(t) = \frac{\sum_{i\in(t,L-1]} h(i)\left|i - m_o(t)\right|}{\omega_o(t)}.$$

C. Extraction of Features

Extraction of features can be referred to as the process of differentiating the different gradients in colours, that is, the various temperatures that are seen as per their respective thermal images. In this, the areas of high temperature zones that are marked with more darker/vibrant shades of colours are differentiated from the areas of lower temperature zones. During the extraction of features, leakages can be detected using the low temperature zones. Leakage normally includes the leakage of oil, coolant, or, up to some extent, even the possible leakage of rocket fuel. Such leakages can prove to be fatal, and are not to be ignored, or considered as false alarms. Figure 5 is a solid example of how Feature Extraction works in both machine, and deep learning.

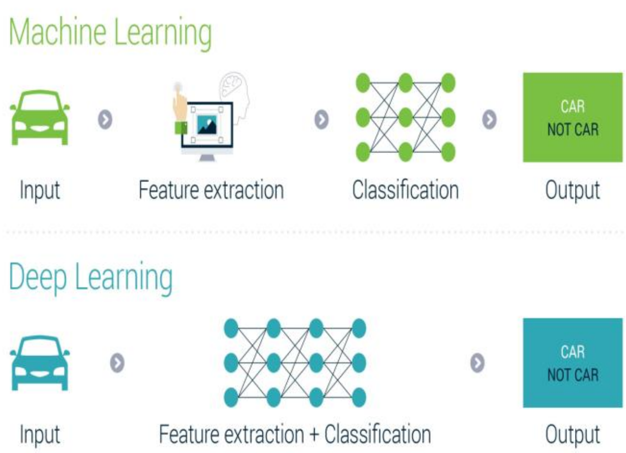

Fig. 5. Feature Extraction - ML v DL

D. Neural Network

Neural Network is mainly used to help a machine or system learn things on how a human brain works, thinks, and interprets things in general. With the incorporation of neural networks and deep learning techniques, it became relatively easy to interpret data in the form of images, that is, in this case, infrared thermal images. The main type of Neural Network incorporated in this system is CNN, i.e., Convolutional Neural Network.

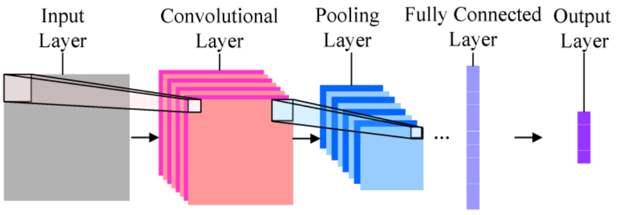

Fig. 6. Convolutional Neural Network

Layers of the Convolutional Neural Network are explained below:

1) Input Layer

In this, the infrared thermal images are fed to the system, and the neural network, as raw input. Each image has a different time stamp, that is, each image is taken at a different instance, which includes before, during, and after lift-off. The system takes these images in the .jpg format, which is the most suitable image format for providing and analyzing the various infrared thermal images. These input images are later fed to the neural network, and are further analyzed and processed in the next layer, which is the Convolution Layer.

2) Convolution Layer

The convolution layer is the main building block of a convolutional neural network (CNN). The convolution layer comprises of a set of independent filters. Each filter is independently convolved with theimage and we end up with 6 feature maps of shape
28*28*1.

3) Pooling Layer

A pooling layer is another important building block of a Convolutional neural network. The function or task of the pooling layer is to reduce the spatial size of the representation so as to reduce the amount of parameters and computations in the neural network. This aids in simplification, and helps build robustness and efficiency. The pooling layer operates independently on each feature map. Max pooling is the approach which is most common.

4) Fully Connected Layer

The fully connected layer in the Convolutional Neural Network (CNN) represents the feature vector for the input which is given to the neural network. This featured layer holds the necessary information that is vital for the provided, or fed input. When the network gets trained, and accustomed to the generally provided input, and input sets, this feature vector is then further used for the general classication and regression. During the training period, or process, the feature vector is used to nd the loss.

5) Output Layer

Once the input is completely processed using the multiple hidden layers of the Convolutional Neural Network, and the data set is properly, and accordingly trained, and once the system is accustomed to the general input of Infrared Thermal Images, which are in the .jpg format, the Output is then finally processed out, in the form of a value, as a result of a myriad of calculations, and prediction algorithms, thanks to the neural network in use.

V. EXPERIMENTAL OUTPUT

Deep learning has been on the rise over the course of half a decade, increasingly becoming popular and reliant at unimaginable speeds. Thus, there is always a better solution to a proposed problem every now and then. This is the main difference between the existing system and the proposed system. While the current system uses slightly similar methods to predict the health of a rocket machinery, or space shuttle, it does not utilize the same degree of efficiency and dexterity of the proposed system.

Most of today's existing systems use only singular layers to process the input infrared thermal images, and aim at predicting or calculating the health of a rocket, whereas, the proposed system incorporates the use of multiple hidden layers within the neural network in question, which is the Convolutional Neural Network (CNN). The existing systems use machine learning for predicting the health of a rocket machinery, or space shuttle, whereas the proposed system utilizes deep learning, which is far more efficient, and convenient to implement and execute.

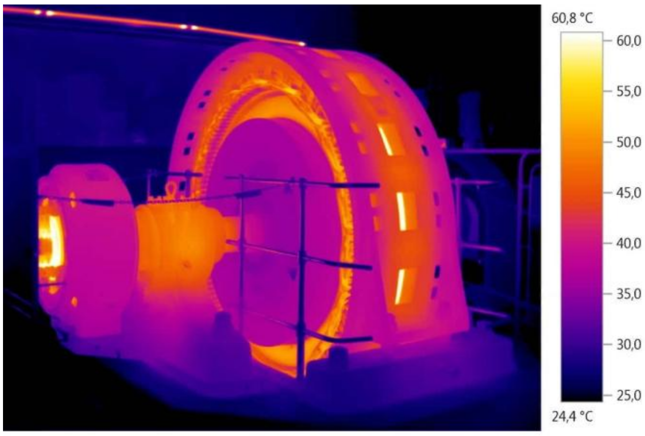

Fig. 7. Infrared Thermal Images Temperature Scale Detection

The proposed system gives a better, accurate and faster results than the existing systems due to use of Convolutional Neural Network(CNN), which makes the system more reliable and efficient than the existing models. The accuracy of the proposed system is greater than 88%, which is better than many of today's existing systems. Accuracy depends on the size of the data set, and the methods used to train the system. The larger the amount of data, the better the accuracy of the system. The provided data set is a huge data set of Infrared Thermal Images of machineries and rockets, or space shuttles, taken at various instances of functioning, which provides a better understanding for the system.

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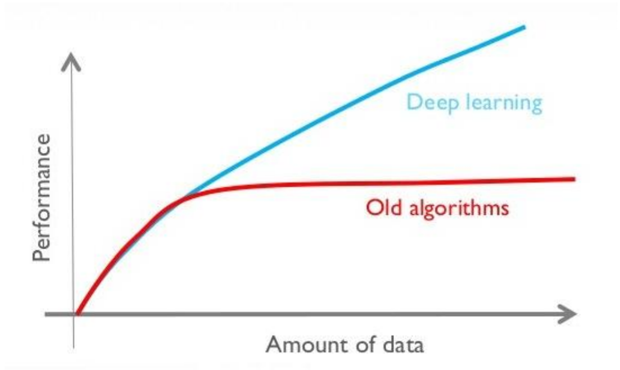

Fig. 8. Increase in accuracy depends on the amount of data

VI. CONCLUSION

Thus, we conclude that the proposed system of Rocket Health Monitoring using Deep Learning for analyzing Infared Thermal Images is an efficient and effective method of determining the health of a rocket. It doesn't incorporate the use of single-layered algorithms, or criteria, to determine the health of the rocket, and its parts, but in fact, using deep learning (CNN), it makes of multiple hidden layers to effectively calculate and

predict the overall health of the rocket, or space shuttle. Various infrared thermal images are taken at different points in time, and for each instance, a different value is generated. This ensures higher accuracy of the resultant estimate.

ACKNOWLEDGMENT

The authors would like to thank Dr. J Jagadeesan, Ph.D., Professor and Head, CSE Department, SRM Institute of Science and Technology, for his continuous support and also for his encouraging and fruitful advises which helped in accomplishing this task.

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