A Novel Architecture for Condition Based Machinery Health Monitoring on Marine Vessels Using Deep Learning and Edge Computing

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Abstract— **Condition based machinery health monitoring on marine vessels involves collecting operational sensor data on the vessel using a robust data acquisition system and determining asset health using anomaly detection analytics. Automation and digitalization of marine vessels involve smart digital technologies such as the Internet of Things (IoT) to collect ships' health data and send it over to a central processing location where this data is analyzed. However, it is difficult to apply this to the shipping industry due to offshore data transmission bandwidth challenges. Deep Learning, a technology that can be used to conduct Machinery Health Monitoring (MHM) holds the key to solve the bandwidth problems. In this paper, we investigate the use of Convolutional Neural Networks (CNN) as a practical solution for deploying Smart Health Monitoring on Marine Vessels using the example of electric induction motors. We show a mechanism to develop data-driven deep learning model that can classify if the motor is in a healthy or faulty condition, and propose an architecture to deploy this model on the Marine vessel in real time on an edge computing hardware. While in operation, sensor data from the motor will be fed into the DL Model, and the resulting predictions will be presented in the Vessel Alarm Monitoring System.**

***Index Terms*—Condition based Machinery Health Monitoring, Marine Vessels, Ships, Convolutional Neural Networks, Deep Learning, Induction Motor, Edge Computing.**

I. Introduction

Shipping Industry has been slow in the adoption of digital technologies like the Internet of Things, Cloud and Artificial Intelligence which are becoming mature in other areas like aerospace, manufacturing, retail, and automotive. Although late to the game, the shipping industry has now started the journey of digital transformation. The year 2018 witnessed several important events that moved the shipping industry closer to digitalization. South Korea announced that it was investing around 700 Million USD into Smart Shipyards that leverage Artificial Intelligence to provide a competitive edge in the global shipbuilding market [1]. US Navy has also undertaken digitalization effort to reduce costs and improve the speed of construction of new generation carriers using technologies such as 3D modeling and Augmented Reality [2]. American Bureau of Shipping (ABS) issued new guidelines to inspect and survey marine vessels using Unmanned Aerial Vehicles. [3]

Smart Digital technologies like Internet of Things involve collection of data related to the object of interest (equipment, human, ship, machine, system or combination thereof) and sent over to a central processing location for analysis and insights. Such intelligence aids in rapid decision making about the system and results in enhanced awareness and operational outcomes that are fruitful to any business. The key factors enabling such vast possibilities are the lower cost of sensors and data storage [2], availability of large computing power and near universal coverage of 4G LTE. A typical architecture of an Industrial IoT solution involves a smart sensor sending data through backhaul communication networks via Corporate LAN or 4G LTE or LoRA, securely to an Industrial Cloud (IoT Platform). Advanced algorithms and Business Intelligence dashboards process and present this data in a user-friendly manner so the consumer can take smart data-driven decisions from anywhere, anytime, and on any device.

ABS has issued Guidance Notes on Smart Function Implementation (SFI) to help guide marine and offshore applications of smart technology [3]. By implementing smart monitoring, vessel and operational data can be leveraged to assist and augment day-to-day operations and be the foundation of a Condition based Maintenance (CbM) program. While this architecture works for many land-based smart solutions, it is difficult to apply this to shipping industry without considerations to data transmission bandwidth challenges. Deep Learning, a technology that can be used conduct Machinery Health Monitoring, also holds the key to solve the bandwidth problems that plague deployment of Smart Applications on Marine Vessels. MHM involves collecting sensor (vibration, temperature etc.) data on the asset while in operation using a robust data acquisition system. This data is then processed and analyzed using algorithms to identify the health indicators that determine if the asset is in normal or faulty operational condition. This process can be divided into the following stages:

- Data collection
- Data processing and transmission
- Analysis of data to develop insights
- Deployment of actions on assets based on insights

In online CbM, this process is highly automated due to the greater availability of communication networks that can backhaul sensor data to CbM experts for analysis. However, due to the scarcity of communication bandwidth present on marine vessels, the transmission of machinery health data from the vessel in real time is a big challenge. We investigate the use of Convolutional Neural Networks (CNN) as a practical solution for deploying SFI on marine vessels. We propose conducting health monitoring on an electric induction motor using CNNs. We intend to develop a data-driven Deep Learning (DL) model that can classify if the motor is in a healthy or faulty condition. Then we propose an architecture to deploy this model on the marine vessel in real time. While in operation, sensor data from the motor will be fed into the DL Model and the resulting predictions will be presented in the Vessel Alarm Monitoring System. This way while the marine vessel is in the voyage, machinery data is analyzed on the vessel itself, and insights provided to Vessel Engineer and Owners in real time, without the raw data having to be transmitted to the shore for analysis.

II. Literature Review

Duy-Tang Hoang et al. propose a CNN to automatically diagnose faults in rolling element bearings. They choose deep learning methodology because, traditional methods involve the use of signal processing techniques by expert knowledge whereas deep learning can learn complex fault detection features by itself. They highlight an important drawback of traditional ML algorithms for fault detection, in that for every fault diagnosis task, feature extractor must be redesigned. These methods also have a shallow architecture thus limiting their ability to learn complex nonlinear relations that exist in fault diagnosis, and hence are hard to generalize when applied to noisy input data. In their method, vibration signals in time domain are transformed into 2-D form, called grey-scale vibration images. Then a CNN is used to conduct fault diagnosis of bearings, which had a fault classification accuracy of 97.7% under low Signal-to-Noise conditions [4].

Olivier Janssens et al. showed that a Deep Learning based system using CNN has more accuracy in fault classification of bearing defects in rotating machinery. They proposed a feature-learning system vis-à-vis feature engineered system, that learns from the raw amplitudes of the frequency spectrum, done on the vibration data. This method yielded an increase of approximately 6% in fault classification accuracy, without relying on human experts in bearing fault detection, to conduct diagnosis [5].

Levent Eren explains that commonly used decision support systems for rolling bearing element fault detection has practical drawbacks that prevent their effective use in real life. Manually extracting fixed features every time data changes, requires a lot of computational time. In addition, if wrong parameters are chosen, then it results in sub-optimal performance of models for fault detection and classification. He proposed a 1D CNN that works directly on raw time-domain vibration data and combines multiple steps like data transformation, feature extraction and postprocessing into a single step. His results indicate that a shallow CNN can achieve high detection rates, and the bearing fault detection exceeds performance offered by traditional classifiers like Multi-Layer Perceptron, Radial Basis Function Networks and Support Vector Machines [6].

Luyang Jing et al developed a CNN that adaptively learns features from raw frequency vibration data in time domain, raw frequency spectrum and their combination, collected on an industrial gearbox. They compare the accuracy provided by CNN to other methods like Fully Connected Neural Network, Support Vector Machine (SVM) and Random Forest, which all involve manual feature extraction by experts. They conclude that a CNN with its feature learning ability and approximately 10% increase accuracy in fault classification compared to traditional methods, can form an end to end deep learning system that can take raw machine health data on a gearbox as input and provide fault diagnosis result as output [7].

Lei Ren et al propose a data-driven, deep CNN to improve the accuracy in prediction of industrial bearing's Remaining Useful Life (RUL). They attempt to find the relationship between RUL expectancy and current working condition of a bearing which typically varies due to operational parameters or environment. Some of the reasons prediction accuracy of RUL is not high is due to large amount of high dimensional data, noise in data, complicated relationship maps that exist in bearing health monitoring scenarios. Due to this traditional signal processing methods and even machine learning approaches fall short, and cannot capture implicit relationships between different features in bearing vibration datasets [8].

ZhiQiang Chen et al. provide an implementation of a CNN for the identification and classification of faults in a gearbox. Different methodologies can be used for machine fault identification such as vibration signature analysis, motor current signature analysis, thermal, noise signature analysis, temperature monitoring and lubrication analysis. Of these, vibration based fault detection is most commonly used as each machine has a normal spectrum until a fault has occurred, and analyzing this change will give insight into the fault condition of equipment. They select features such as RMS values, standard deviation, skewness, kurtosis, rotation frequency and applied load and feed these as a 2D vector to a CNN. They group individual faults on gears and bearings into various faulty condition patterns and develop a classifier to accurately predict a pattern, based on input data. They experiment with different CNN architectures and parameter tuning and achieve gearbox fault diagnosis classification accuracy of over 98% [9].

In [11], CNN based deep learning scheme is proposed by Yong Yao et.al to identify fault pattern in the gears. Raw signals in time and frequency domains are directly given to the model using end-to-end CNN without traditional acoustic-based gear fault diagnosis schemes that require prior knowledge of the model as well as the signal processing technique. Results achieved using the proposed scheme validate its effectiveness by showing better fault diagnosis performance as compared with traditional schemes involving feature engineering.

Nikou Gunneman et.al suggest a CNN based approach to predict the engines' damage using multi-view and highly imbalanced signals coming from the internal engine excitation. Real-word case study data based experimental results exhibit the effectiveness of the proposed algorithm in detecting the engines' defect. Authors utilized a combination of data level and cost sensitive approaches to deal with the imbalance problem [12].

III. Convolution Neural Network

Deep Learning [19] is one of the most important developments in Artificial Intelligence in recent years. It is a branch of Machine Learning and uses a set of algorithms that attempt to model and learn patterns in high dimensional data using large computing power.

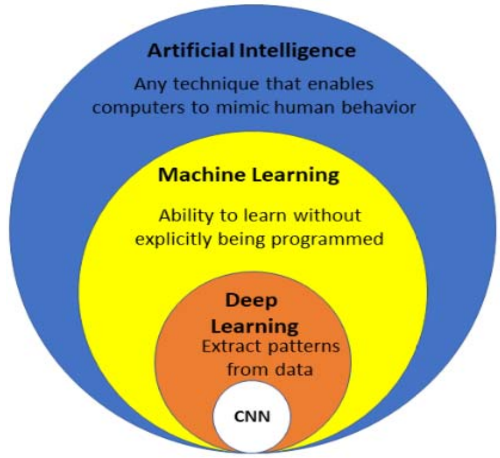

Fig 1. Relationship between Convolution Neural Network and Artificial Intelligence [13]

In a regular artificial neural network, the input is usually transformed to output through a series of layers. Each layer has a fixed number of neurons and each neuron is connected to every other neuron in the previous and next layer. While this architecture works for processing relatively normal datasets, it becomes computationally expensive when applied to computer vision and image classification problems. In 1998, Yann LeCun et al [14] introduced a different kind of neural network architecture called LeNet-5 which has subsequently become known as Convolution Neural Network (CNN). It consisted of convolution and average pooling layers, followed by a flattening convolution layer, two fully connected layers and finally a soft-max classifier.

A typical CNN consists of one or more convolution layers followed by sub-sampling steps and then followed by a fully connected layer where final classification decision takes place, like in a multilayer perceptron network. This architecture is especially suited to take advantage of the 2D structure of an input image or a speech signal or a vibration signal. The main components of a CNN are as below:

- Convolution Operation
- Kernel or Filters
- Pooling
- Activation Function
- Classifier

IV. Proposed Architecture For Fault Diagnostics in Induction Motors

Ship owners and operators are interested in minimizing maintenance costs while maximizing the outcomes provided by active maintenance. An European Funded Project called INCASS (Inspection

Capabilities for Enhanced Ship Safety) addresses the issues of inspection and monitoring of ship structures and onboard machinery [18]. The consortium proposed a framework for conducting enhanced inspection using robotic platforms using intelligent' sensors to collect structural and machinery health data as part of Structural and Machinery Risk Analysis (MRA). Outputs from this can be fed as early warning signs to a Decision Support System, from which ship owners or operators can take actions.

Condition based machinery health monitoring (MHM) generally involves collecting data about the machine or system (induction motor, pump, engine, gearbox, blower, chiller, compressor etc) and analyzing it to gain insights into its ongoing performance and detect any degradation. Many technologies can be used to assess the condition of machinery such as vibration, current, temperature and thermal monitoring, as well as lubrication oil analysis. Of these, it is widely accepted that vibration data can provide valuable insights into many machinery fault detection and diagnostics. The main thing to note with vibration data analysis, is the sheer amount of data that is generated. For example, ten vibration sensors(accelerometers) sampled at 40KHz for 10mins on a gear box drive train can generate as much as 1.5GB of data [10]. If a similar gear box was on a marine vessel, it will be impractical to send this much data continuously to shore, for analysis by machinery health specialists.

Edge Computing is a concept where sensor data is gathered, processed and analyzed as close to the place where it was created. That in combination with Deep Learning holds the key for online implementation of machinery fault detection and diagnostics with vibration data for various rotating equipment including induction motors.

Electrical Induction Motors are arguably the workhorses of modern power drive transmission industry. A 3-phase induction motor is either used alone or more often coupled with another equipment like pump or gearbox etc. to provide necessary power transmission functions [20]. A squirrel cage motor is rugged, has no commutators and used for constant speed drive systems. With the availability of solid state controllers, they are also being used in variable drive systems. Induction motors typically operate in harsh, continuous and rugged environmental conditions and hence are constantly subjected to varying operating profiles that make them susceptible to failure or breakdown. These conditions include overload, poor lubrication, insufficient cooling, frequent start and stops etc. Electric Power Research Institute (EPRI) conducted a study in 1985 and found that 41% of faults were in bearings, with 37% in stator followed by 10% in rotor. IEEE standard 493-1997 lists similar findings summarized in Table 1.

Table I. Statistics on motor faults/failure modes [15]

Types of faults	Number of faults/failures				
	Induction motor	Synchronous motor	Wound rotor motors	DC Motors	All motors
Bearing	152	2	10	2	166
Winding	75	16	6	--	97
Rotors	8	1	4	-	13
Shaft	19	-	--	-	19
Brushes or slip rings	--	6	8	2	16
External device	40	7	1	-	18
Others	10	9	--	2	51

The various types of faults that occur in an induction motor have been classified and detected by vibration and motor current signature analysis [16].

We propose a novel architecture for onboard ship CbM with automated fault diagnosis of an induction motor for example. This is divided into two stages.

1. Collection of healthy and faulty induction motor data to develop a CNN capable of performing fault detection and diagnosis.
2. Deployment of CNN model on board the vessel in edge computing hardware, and connecting its predictions or outputs to Vessel Alarm Monitoring System (VAMS).

A. *Stage 1*

Vibration data on induction motor can be collected in a laboratory setting or in field (i.e. dry dock or at port) while the vessel is at shore. Based on the motor type, historical failure data, a list of various faults that can happen on this motor should be compiled. Depending on motor speed at output shaft, suitable accelerometers should be chosen that can sample at least twice that of the fault occurring frequency, due to Nyquist criteria. Care should be taken to ensure that the accelerometer's frequency range, covers any possible harmonics of interest. While looking for bearing related faults, ball spin frequency(BSF), ball pass frequency outer ring(BPFO), ball pass frequency inner ring(BPFI), cage fault frequency(CFF) etc. should be calculated, and ensured that the chosen data acquisition hardware is suitable to collect vibration data, from which these signatures can be found out. From the vibration data collected, a 2D image is constructed, which is fed into a Convolution Neural Network. Loss function, optimizer, classifier and other hyper parameters are suitably tuned during the training process. The CNN learns the features relevant to a fault code and prediction accuracy of classifier is evaluated. Once it is determined that the classification accuracy is acceptable, it is usually converted into a

Predictive Model Markup Language (PMML) format, so that it can be deployed across wide range of edge computing capable hardware as shown in Fig 2.

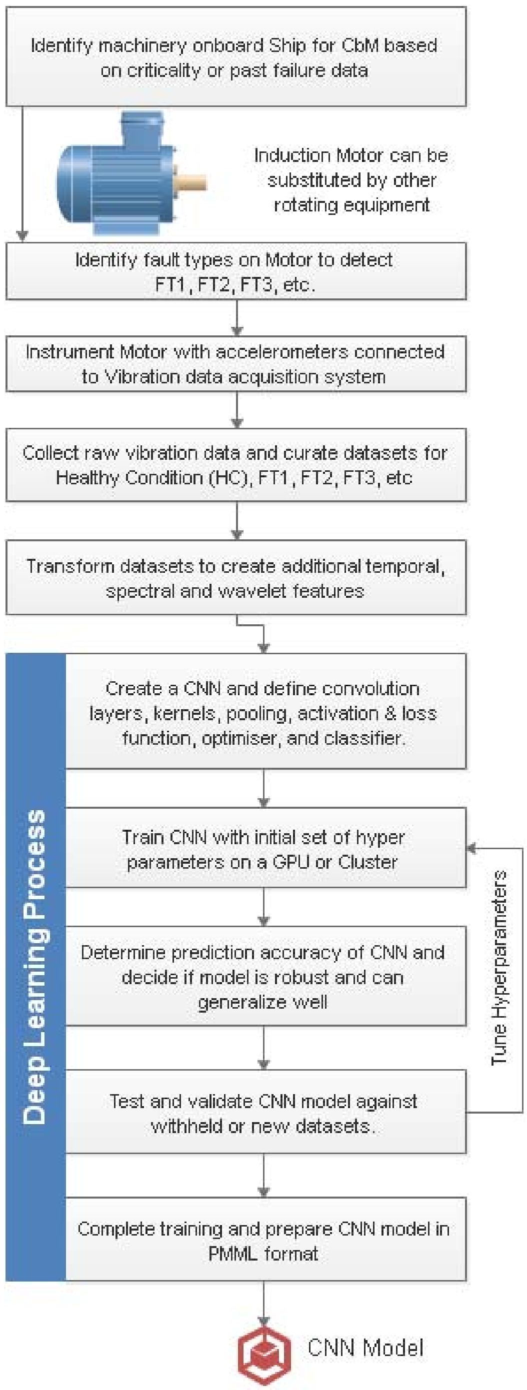

Fig 2. Development of CNN for FDD

B. Stage 2

Once the CNN model is ready, it can be deployed on any hardware (Edge Gateway) that can perform 'inference' or 'prediction' on the edge. This hardware is expected to be on the vessel network, and will communicate its output to the VAMS on a periodic basis. Accelerometers will be physically mounted on the induction motor(s) and vibration data captured about the motor is transmitted to Edge Gateway either through wired or wireless protocols like WiFi or MQTT. The Gateway will also have capability to keep track of prediction accuracy for every inference it is making, and this log can be uploaded or sent to shore on a periodic basis. The idea is to ensure that the deployed CNN model has still sufficient accuracy and need not be replaced with a new version as shown in Fig.3.

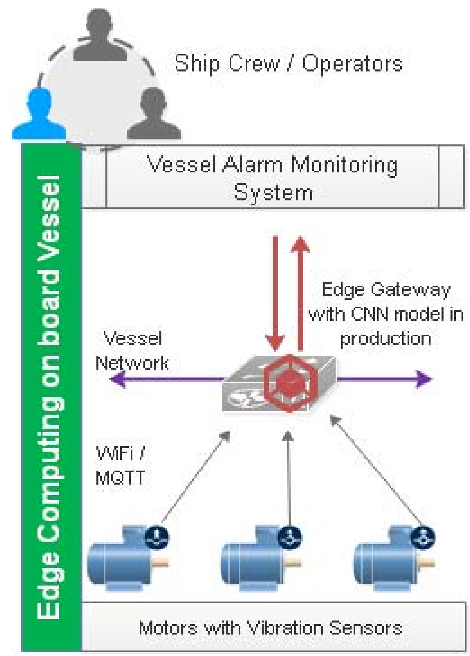

Fig 3. Deployment of CNN on Edge Gateway on board vessel

V. Conclusion

This paper has proposed a novel architecture for condition based machinery health monitoring on marine vessels using Deep Learning and Edge Computing. To mitigate connectivity problems on marine vessels due to difficulty of sending data to cloud, we presented a CNN based architecture that is capable of identifying abnormal conditions in near-real time with high specificity The advantage of this architecture, is its applicability to any scenario where assets are in remote locations, with poor connectivity, which is typically the case in other industries like Mining, Oil & Gas and Aerospace.

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