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Beam Pump Dynamometer Card Prediction Using Artificial Neural Networks

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Abstract

A beam or a sucker rod pump is an artificial-lift pumping system using a surface power source to drive a downhole pump assembly. A beam and crank assembly creates reciprocating motion in a sucker-rod string that connects to the downhole pump assembly. The pump contains a plunger and valve assembly to convert the reciprocating motion to vertical fluid movement. A dynamometer is a diagnostic device used on sucker rod pumped wells that measures the load on the top rod and plots this load in relation to the polished rod position as the pumping unit moves through each stroke cycle. The analysis of the dynamometer card data has valuable insights on the status of the pump and indicates if future actions are needed. This study was done using artificial neural networks, a subset area of machine learning, for categorizing beam pump operating conditions based on dynamometer card data to provide a planning horizon for future operational and facility actions.

Keywords: Artificial Intelligence, Beam Pump, Big Data, Convolutional Neural Network, Deep Learning, Sucker Rod

1. Introduction

Oil is a vital asset to the global energy needs. The oil industry has a wide range of activities including but not limited to exploration, extraction, refining, and marketing. The extraction of oil is the process by which oil is drawn out from beneath the Earth's surface.

When natural drive energy of a reservoir is not sufficiently strong to push oil to the ground surface, an artificial lift process is used on an oil well to increase reservoir pressure to draw the oil to the surface.

The oldest and most widely used type of artificial lift is called beam pumping, or the sucker-rod lift method. The dynamometer card, or pump card, displays the fluid load on the pump plunger over a pump cycle. It is a plot of the calculated loads at various positions of a pump stroke. The size and shape of the card indicate the operating conditions and performance of the pump.

Identification and diagnosis of beam pumps using the valuable pump card is an expensive human visual interpretation process. It does not only require a lot of labor time but also requires deep expertise in the domain. The process, just like any other process involving human visual interpretation is also prone to errors. In addition, oil fields are increasingly generating more data from real-time sensors or IoT (internet of things), making it harder for human experts to handle and interpret this large data.

Therefore, utilizing pattern recognition techniques can significantly help automating the visual interpretation process, increasing efficiency and reducing maintenance activities due to missed early diagnosis.

ImageNet Challenge is an annual large scale visual recognition challenge where research teams evaluate their algorithms on a given dataset, with over 1.2 million images and 1,000 classes.

Several winning artificial neural network based algorithms have been open-sourced to the public after the annual competition. These pre-trained algorithms keep proving their success and astonish the scientific community with their ability to surpass human capability to perform image classification in domains like autonomous driving, healthcare, retail, and many others.

2. Literature Review

There are a number of studies that have focused on performing pattern recognition in the domain of dynamometer cards for many years. These methodologies can be mainly split into three categories:

2.1. Rule-based methods

These methods can, for example, be based on selected descriptors of the dynamometer cards like contour (border) or region (de Lima 2012). Descriptors like centroid, curvature, K-curvature are used. Euclidean distance, or Pearson correlation are used as mathematical tools for calculating similarity.

2.2. Machine learning with manual feature extraction

Machine learning is based on algorithms that can learn patterns from data (Tian 2007, Li 2013). Manual feature engineering is required such as dividing dynamometer cards using the "four point method" (Li 2013) and then extracting moment invariants for pattern recognition using a support vector machine (SVM), a popular machine learning algorithm.

2.3. Deep learning with automatic feature extraction

Deep learning based approaches automatically extract features of dynamometer cards using state-of-the-art artificial neural networks. Convolutional neural networks (CNNs), a class of deep, feed-forward artificial neural networks use a variation of multilayer perceptron designed to require minimal preprocessing. These CNNs have been studied on the dynamometer card problem with data-based and image-based methodologies (Hangqi 2017).

Other types of custom feed-forward artificial neural networks have been used (Bezerra 2009).

Most of the methods used in category 1- Rule-based methods and category 2 - Machine Learning, as aforementioned, require extensive human-performed feature engineering.

Studies conducted in category 3 - Deep learning with automatic feature extraction, as aforementioned, were a step ahead and improved by automating feature extraction and showed noticeable improvement in accuracy.

However, the studies conducted using deep learning have mostly used neural networks trained from scratch. Some of the work that was performed required over 1,440 epochs/iterations for the neural network to converge (Bezerra 2009).

Transfer learning is a branch of machine learning which relies on utilizing knowledge gained in solving one problem, and applying it to a different but related problem (Q. Yang 2009). For example, an artificial neural network can be trained to recognize cats. The same trained network can be then used to train another classifier to detect dogs, and can converge much faster than training the network from scratch.

This work adopts a combination of convolutional neural networks based deep learning and transfer learning based on ImageNet datasets to build classifiers that can detect and classify beam pump conditions based on images of pump card dynamometer shape.

Different types of classifiers are used on our dataset and results are compared. A number of deep learning techniques that significantly help a neural network to converge and reduce over-fitting are presented. Most of these relatively new techniques are used in research and online data science competitions to achieve world-class accuracy in image classification problems.

3. Framework and Research Methodology

This section elaborates more on the dynamometer card classification problem definition, provides details about the dataset, specifies software and hardware requirements used in research, and finally briefly discusses different neural networks and deep learning techniques used.

3.1. Problem definition

A beam and crank assembly creates reciprocating motion in a sucker-rod string that connects to the downhole pump assembly. The pump contains a plunger and valve assembly to convert the reciprocating motion to vertical fluid movement. Figure (1) shows standard sucker-rod artificial lift operation and Figure (2) shows how its movement is represented in a pump card.

There are over twenty (20) different main classifications that describe the operating conditions of a pump card. These categories are well known by domain experts. They can be visually differentiated. In some cases, more than one phenomena can co-exist in the beam pump (a pump may be in two classifications). In deep learning, this can be introduced as a new classification defined by the shape combining the other two classifications.

For the purpose of this research, we use a total of eight (8) different commonly known classification categories (excluding when two classifications may co-exist in a pump):

1. Normal operation
2. Slight gas interference
3. Severe gas interference
4. Severe fluid pound
5. Standing valve leak

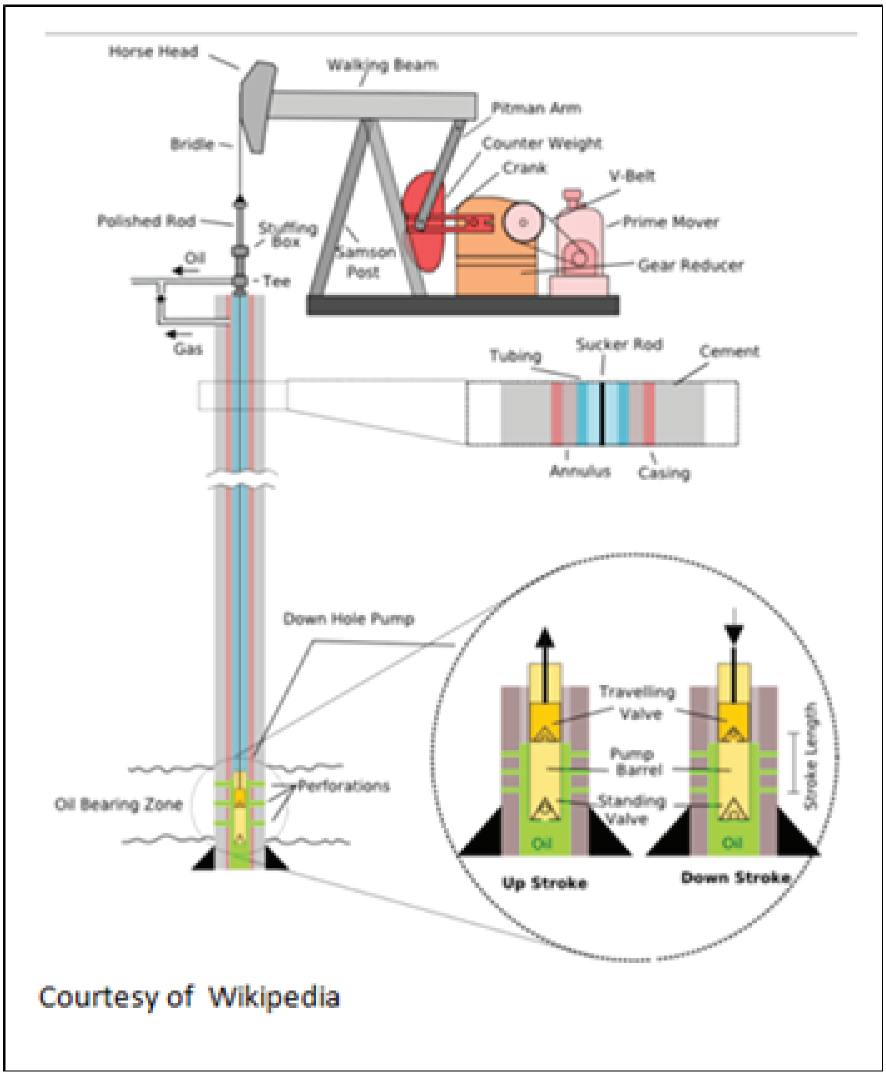

Figure 1: Sucker-rod standard artificial lift operation.

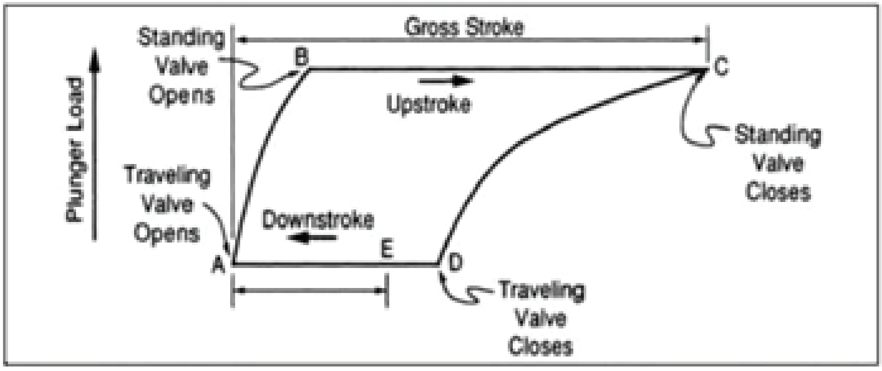

Figure 2: Pump card upstroke and downstroke (Economides el al., 1994).

6. Worn pump
7. Stuck piston
8. Sand production

Pump card sample shape for each of the above categories is shown in Figure (3). For each of the eight (8) shapes shown, the x-axis denotes displacement and the y-axis denotes load (both axes are not shown in the figure). The area inside the shape is filled in black for the purpose of image CNN classification.

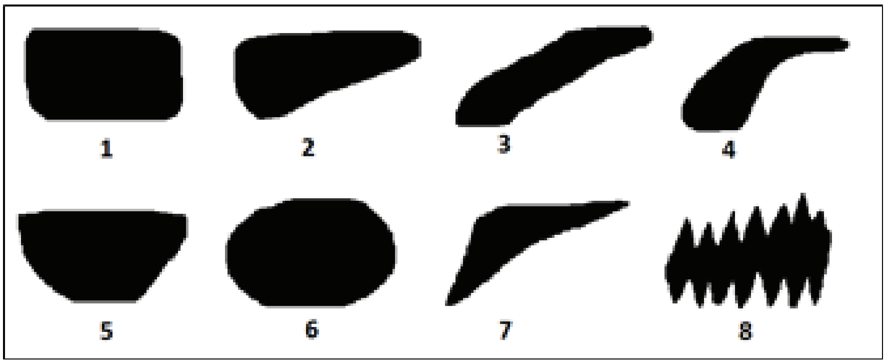

Figure 3: Examples of different shapes of pump card.

3.2. Data collection and dataset

While most deep learning practitioners use large datasets for training, due to limitations on getting a larger labeled dataset, a relatively small dataset is used for this research composed of eighty (80) images for training, and sixteen (16) other images for validation (two per classification). The whole dataset is composed of ninety six (96) images.

The dataset is split into two main folders (1) training and (2) validation. The training folder has eight folders representing the eight categories, with each category having ten pump card shape images. Similarly, validation folder has eight folders with each having two (2) images to test the deep learning model prediction accuracy.

The data is collected from an Open Platform Communications (OPC) server which collects pump card data from beam pump sensors in real-time. The pump card data of load and displacement is stored in files, and then pump card shape is plotted. The resulting image with black fill is saved as a 256 x 256 pixels PNG image.

3.3. Software and hardware requirements

There are a number of open source deep learning libraries that allow researchers to experiment with deep learning and transfer learning techniques. Pytorch is an open source deep learning library for Python, based on Torch. It is primarily developed by the artificial-intelligence research group at Facebook.

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Pytorch is chosen as the deep learning library used in research as it has many pre-trained deep learning models that can be used for experimenting with transfer learning using convolutional neural networks. FasiAI is a high level deep learning framework that uses Pytorch library with an abstraction from low level programming. It is used as a convenient interface for Pytorch, providing all Pytorch features in a flexible and easy to use abstraction.

Jupyter Notebook is an open-source web application that allows data scientists to program in Python through a web-interface. It is used to interact with FastAI with Pytorch engine, visualize the pump card images, and evaluate the quality of deep learning models trained.

For hardware, an Amazon Web Services (AWS) Elastic Compute Cloud (EC2) p2.xlarge machine with one (1) GPU is used for building deep learning models as part of this research.

3.4. Methodology and deep learning models

Three different types of convolutional neural networks (CNNs) are used with the same number of epochs, learning rate, loss, data augmentations, and test time augmentations (TTA) for the purpose of this research. All models used are pre-trained on an ImageNet dataset. Due to the small dataset used, the focus is more on probing the potential of using CNNs and comparing their performance on the used pipeline rather than getting the highest accuracy possible or fine-tuning a model to its maximum performance.

The following briefly sheds a light on the different pre-trained CNNs used for classification:

3.4.1. VGG16

VGG16 (also called OxfordNet) is a CNN named after the Visual Geomtry Group from Oxford (Simonyan 2014). The group used it to win the ImageNet competition in 2014. VGG16 is a very deep network with a lot of convolution layers followed by max-pooling that reduces dimensionality. Figure (4) shows VGG16.

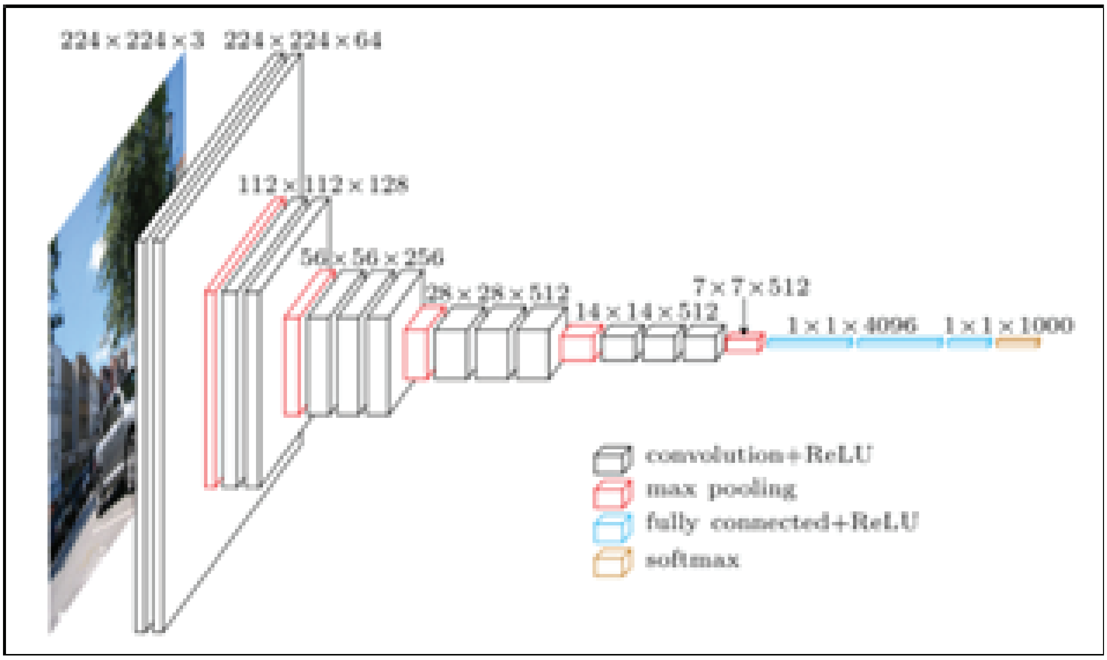

Figure 4: VGG16 Architecture.

3.4.2. ResNet34

ResNet won the first place in ImageNet competition in 2015. A residual neural network (He, Kaiming et al 2016) helps preserving good results through a very deep neural network. It uses skip connections to solve vanishing gradient problem. ResNet34 is a thirty (30) layer residual network. Figure (5) shows a Residual Building Block.

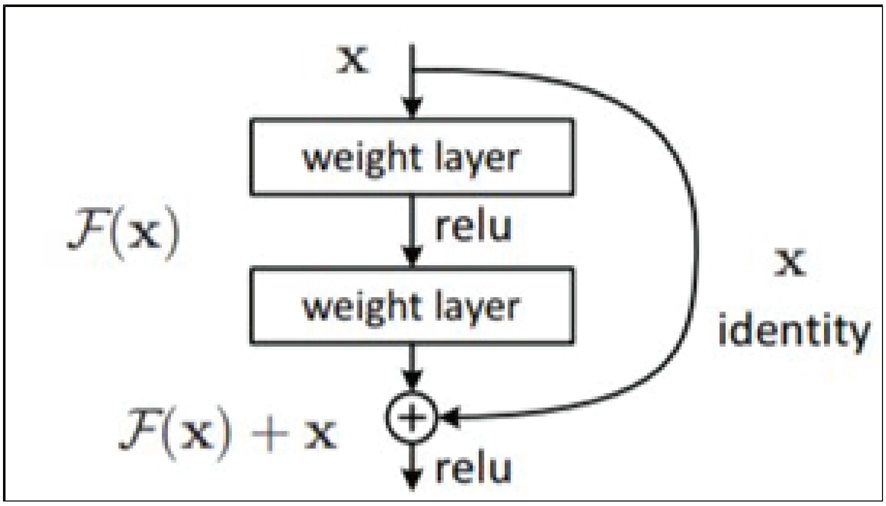

Figure 5: Residual Learning: a building block (He, Kaiming et al 2016).

3.4.3. ResNeXt50

ResNeXt came at the second place in ImageNet 2016. ResNeXt introduces a new term called “cardinality” (Xie 2017). In theory, increasing cardinality is able to improve classification accuracy. Figure (6) shows the difference between a ResNet block and a ResNeXt block.

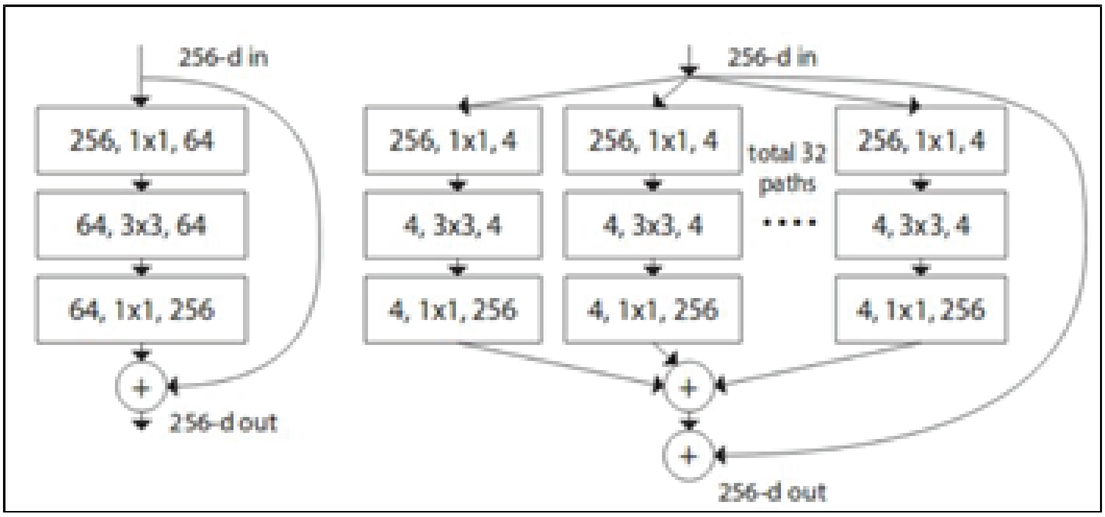

Figure 6: ResNet (left) and ResNeXt (right) Architecture (Xie 2017).

The following explains the deep learning pipeline used for each of the previously mentioned CNNs:

1. Load all images and resize to 224 (most convolutional neural networks prefer this input)
2. Train last layer of classifier on the training data (80 images) and evaluate on validation (16 images) using gradient descent with 0.01 learning rate for two (2) epochs.
3. Find an optimal learning rate using Cyclical Learning Rates (Smith, L. N. 2015).
4. Use data augmentation to train last layer (3 epochs with cycle length = 1). Data augmentation refers to creating more data using augmentation by randomly changing the images using flipping, zooming and rotations without impacting their interpretations. This helps prevent the over-fitting of a model. Figure (7) shows different types of augmentations on the same image. This is just like how a human can interpret the pump card shape whether the image is rotated or not. This helps the deep learning model to converge by providing additional data for training.

5. Unfreeze all layers (previous steps were training only on last layer)
6. Set earlier layers to 3x-10x lower learning rate than next higher layer.
7. Find best learning rate again and train full network with two (2) cycle multipliers until over-fitting.
8. Use test-time-augmentation which randomly augments validation data set and predicts original and augmented images, and then averages predictions from these images.

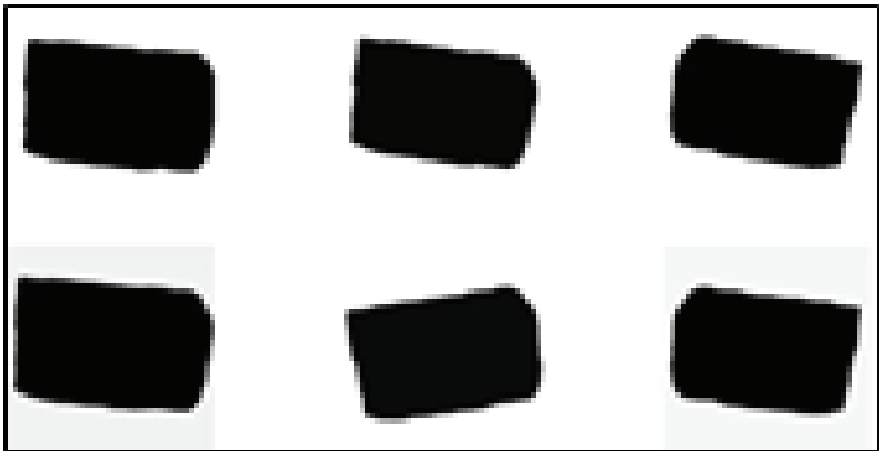

Figure 7: Different Types of Augmentations.

4. Research Findings and Discussions

As a first investigation of results, the overall prediction accuracy after step (8) from section above, TTA, of each CNN model is shown in Table I.

Table 1: Deep Learning CNN Models Accuracy.

Model	VGG16	ResNet34	ResNeXt50
Accuracy	87.5	100	56.25

Table I shows that the best model is ResNet34. However, that does not mean that other models may not be able to achieve similar results. VGG16 and ResNeXt50 may take more time to converge. For the sake of this research, we conclude that ResNet34 performs better since it converges faster than other predictive deep learning models. A larger dataset may show different results since our dataset is quite small for deep learning models which are usually used for big data.

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For further investigation, we plot the confusion matrix for each of the three CNNs. The confusion matrix is a table that allows visualization of the performance of an algorithm making it easy to see if the deep learning system is confusing two classes.

Figure (8) shows the confusion matrix for VGG16, ResNet34, and ResNeXt50 respectively.

We further explore the performance of different CNN models after performing step (2), training the last layer of the classifier with a pre-trained model for two (2) epochs.

Table II shows each model's accuracy at that stage.

Table 2: Deep Learning CNN Models Accuracy after 2 Pre-trained epochs on Last Layer.

Model	VGG16	ResNet34	ResNeXt50
Accuracy	43.75	68.75	87.5

We can observe that at that early stage of training only the last layer with a pre-trained model, ResNeXt50 seems to give the best performance, followed by ResNet34, and then VGG16.

Nevertheless, towards the end of training pipeline after unfreezing early layers, it seems that ResNeXt50 has some challenges in quick convergence compared to VGG16 and ResNet34. This does not necessarily mean that ResNeXt50 may not perform better than the other two CNNs. It may simply require more time to converge due to the complexity of its network architecture. It is commonly known that training early layers takes more time to converge since these layers were pre-trained and finding the right weights for a deep neural network can take much longer than fine-tuning last layers of the network. Over-fitting when dealing with a small dataset is also a concern and the performance of a CNN on a small dataset cannot be guaranteed on a larger dataset.

In a last investigation, we look at the most uncertain prediction of the two best performing models after training the last layer with a pre-trained model for 2 epochs (with no augmentation, cyclic learning rate, nor test time augmentations). Figure (9) shows the most challenging images (or most uncertain predictions) for ResNet34 and ResNeXt50 respectively.

5. Conclusion

This paper has reviewed and analyzed the potentials of using artificial neural networks, specifically convolutional neural networks combined with transfer learning, for eliminating the need for manual feature engineering and fast convergence when building a

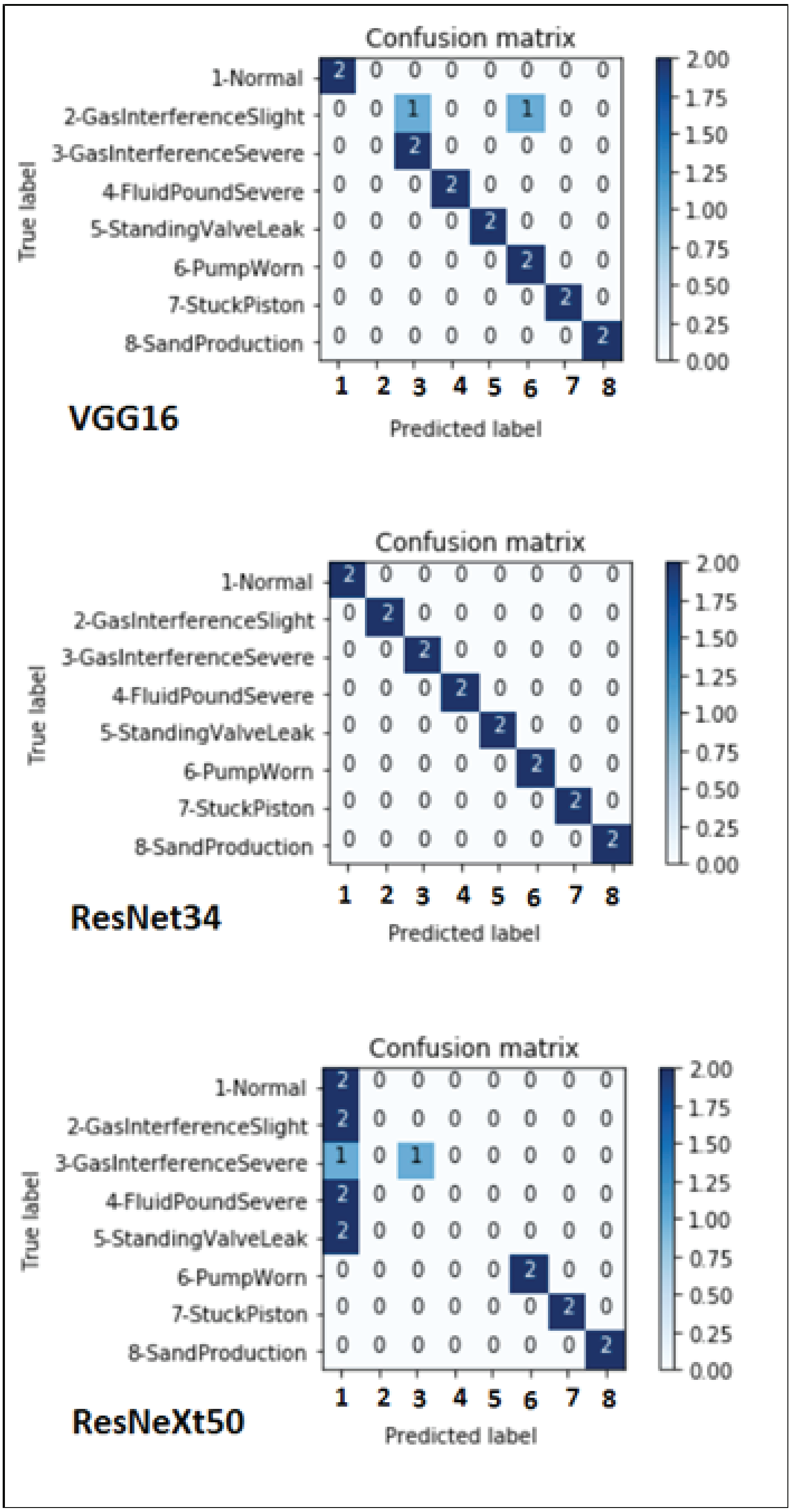

Figure 8: Confusion Matrix for VGG16, ResNet34, and ResNeXt50.

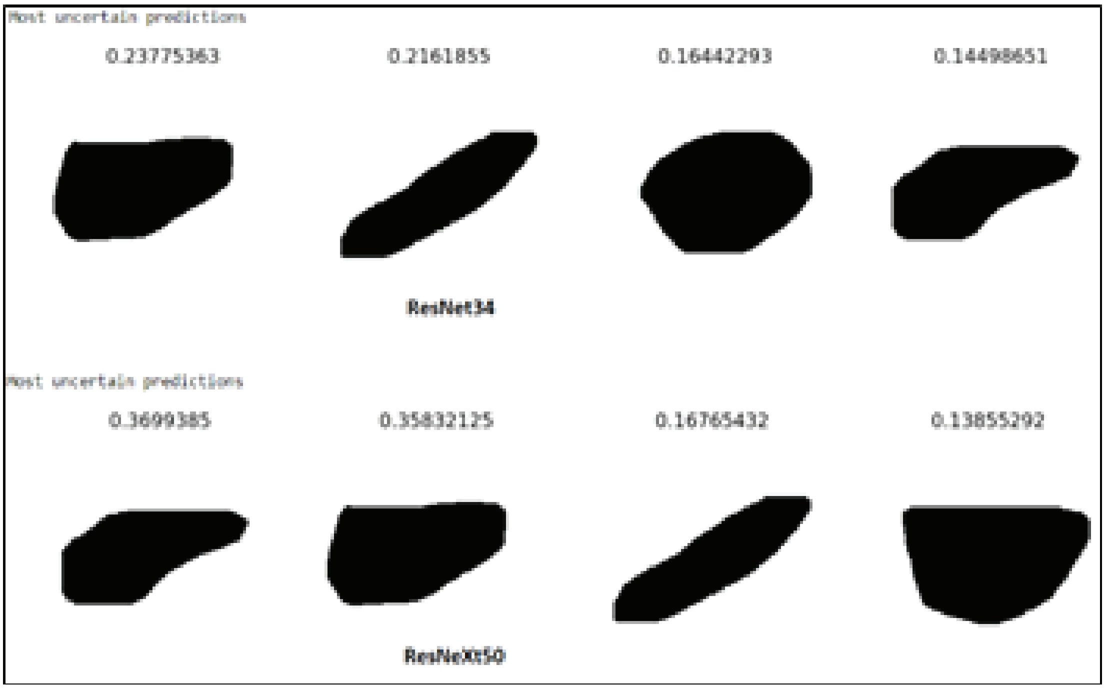

Figure 9: Most Uncertain Predictions for ResNet34 and ResNeXt50 after Last Layer Training with Pre-trained Model.

system to automatically classify beam pump conditions based on a pump card shape provided as an image.

Although using a limited dataset, the results show promising potential for further work. In a typical oil field, there may be hundreds of beam pumps deployed which require continuous robust diagnosis. Lack of experienced resources, cost, and wrong interpretations could all be eliminated using an artificial intelligence system that can proactively monitor the whole fleet of pumps and provide early notifications of problems.

Further work can explore the performance after increasing the size of the dataset. It can also explore adding more complex categories for classification. Moreover, future work can also look at adding different type of sensor data, well test data, or temperature to help building better models. Finally, the same pump card data collected as time-series can be used to make future predictions of the status of a pump operating conditions using advanced sequence models like recurrent neural networks and specifically long-short-term-memory (LSTM) neural networks.

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