# VISVESVARAYA TECHNOLOGICAL UNIVERSITY

# BELAGAVI

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**Project Synopsis**

**On**

**“Hydrocarbon Exploration using Seismic Imaging”**

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**Bachelor of Engineering**

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**Hydrocarbon Exploration using Seismic Imaging**

**ABSTRACT**

Seismic-data interpretation has as its main goal the identification of compartments, faults, fault sealing, and trapping mechanism that hold hydrocarbons; it additionally tries to understand the depositional history of the environment to describe the relationship between seismic data and a priori geological information. Imaging salt has been a huge topic in the seismic industry, basically since they imaged salt the first time. The Society of Exploration geophysicist alone has over 10,000 publications with the keyword salt. Salt bodies are important for the hydrocarbon industry, as they usually form nice oil traps. So there's a clear motivation to delineate salt bodies in the subsurface. Seismic data interpreters are used to interpreting on 2D or 3D images that have been heavily processed. In our problem statement we our dealing with data that is less noisy which is an added advantage. Our solution to the problem is to basically use U-Net. The energy function is computed by a pixel-wise soft-max over the final feature map combined with the cross entropy loss function. The soft-max is defined as (x) = denotes the activation in feature channel k at the pixel position x ∈ Ω with Ω ⊂ . K is the number of classes and (x) is the approximated maximum-function.

**INTRODUCTION**

Seismic data is collected using reflection seismology, or seismic reflection. The method requires a controlled seismic source of energy, such as compressed air or a seismic vibrator, and sensors record the reflection from rock interfaces within the subsurface. The recorded data is then processed to create a 3D view of Earth's interior. Reflection seismology is similar to X-ray, sonar and echolocation. A seismic image is produced from imaging the reflection coming from rock boundaries. The seismic image shows the boundaries between different rock types. In theory, the strength of reflection is directly proportional to the difference in the physical properties on either sides of the interface. While seismic images show rock boundaries, they don't say much about the rock themselves; some rocks are easy to identify while some are difficult. There are several areas of the world where there are vast quantities of salt in the subsurface. One of the challenges of seismic imaging is to identify the part of subsurface which is salt. Salt has characteristics that makes it both simple and hard to identify. Salt density is usually 2.14 g/cc which is lower than most surrounding rocks. The seismic velocity of salt is 4.5 km/sec, which is usually faster than its surrounding rocks. This difference creates a sharp reflection at the salt-sediment interface. Usually salt is an amorphous rock without much internal structure. This means that there is typically not much reflectivity inside the salt, unless there are sediments trapped inside it. The unusually high seismic velocity of salt can create problems with seismic imaging.

**STATEMENT OF THE PROBLEM**

Several areas of Earth with large accumulations of oil and gas *also* have huge deposits of salt below the surface.

But unfortunately, knowing where large salt deposits are precisely is very difficult. Professional seismic imaging still requires expert human interpretation of salt bodies. This leads to very subjective, highly variable renderings. More alarmingly, it leads to potentially dangerous situations for oil and gas company drillers.

**WHY IS THE PARTICULAR TOPIC CHOSEN?**

In previous implementations accuracy is estimated using 10-fold cross validation [4]. The classification model was subsequently used to automatically label the entire body of seismic data (376,752,501 voxels). Our top performing learning algorithms were the following: Gradient Boosting Trees (Accuracy 80%), Extremely Randomized Trees (Accuracy 80%), and Random Forests (Accuracy 79%). All our learning algorithms are ensemble methods; these techniques have shown remarkable performance due to their ability to attain low bias (using complex decision boundaries), and low variance (achieved by averaging over various models) [1].

Since the presence of salt increases the likelihood of finding oil and gas deposits below that segment of the surface, Oil and Gas Companies can benefit from this by wisely choosing the segments of the land that contains more amount of Oil deposits, thereby making effective and rational use of company resources.

**OBJECTIVE AND SCOPE OF THE PROJECT**

Our main objective is to identify such potential segments of land that contain significant amount of salt based on the images of the land segments provided as input.

Oil and Gas Companies can benefit from this by wisely choosing the segments of the land that contains more amount of Oil deposits, thereby making effective and rational use of company resources.

**METHODOLOGY**

1. *Preprocessing*

Our approach aims at automatically identifying and delineating geological elements from seismic data. Specifically, we focus on the automatic classification of salt bodies using supervised learning techniques [3]. In supervised learning we assume each element of study is represented as an n-component vector-valued random variable (X1, X2,..,Xn), where each Xi represents an attribute or feature; the space of all possible feature vectors is called the input space **X**. We also consider a set {w1, w2,...,wk} corresponding to the possible classes; this forms the output space **W**. The dataset we have obtained contains a set of PNG files, each image having a resolution of 101 x 101. Since we are using a U-Net we will need to convert each of them to 128 x 128. The main reason is symmetry of the U-Net i.e concatenation has to be done on equal sizes. 101 is really tedious to prime factorize even considering neighbour's without intermediate resampling or huge strides. The images in the dataset are compressed using Run-Length encoding, which is a form of lossless data compression in which runs of data (that is, sequences in which the same data value occurs in many consecutive data elements) are stored as a single data value and count, rather than as the original run. These images need to be decompressed and stored in binary format.

1. *Plot the depth distribution in the training data :*

Our data analysis phase receives as input a body of seismic data with the task of automatically identifying salt regions. We randomly sample a small fraction (0.5%) of the total data. To achieve a class-balanced problem, we plan to make sure exactly one half of the subset corresponded to salt, and the other half as non-salt (the task exhibited equal class priors). Then we plot the values of the depth attribute indicating how deep most of the salt bodies. This will help us generalize saying that most salt bodies lie in x to y range.

1. *Plot the proportion of salt vs depth in the training data :*

We will also need to apply masks on the images as the masks are easier to process by the neural network than the raw images. These maskswill be in black and white; making it easier to detect where salt is present and where it isn’t. Further on we will plot the proportion of salt vs depth to find out the actual correlation between them.

1. *Building the U-Net algorithm:*

While choosing our model for training it was clear that we needed a deep convolutional neural network.[2]. Something like AlexNet, VGG-16, VGG-19, Inception Nets, ResNet, Squeeze Net etc. But we have decided to go with U-Nets[5]. U-Net is considered one of standard architectures for image classification tasks, when we need not only to segment the whole image by its class, but also to segment areas of image by class, i.e. produce a mask that will separate image into several classes. It’s architecture is input image size agnostic since it does not contain fully connected layers. Because of many layers takes significant amount of time to train. U-Net is designed like an auto-encoder. However, in contrast to the autoencoder, U-Net predicts a pixel wise segmentation map of the input image rather than classifying the input image as a whole. For each pixel in the original image, it asks the question: “To which class does this pixel belong?’’. This flexibility allows U-Net to predict different parts of the seismic image (salt, not salt) simultaneously.

**POSSIBLE OUTCOMES**

* Segments Regions of Land that contain significant amount of salt.
* Segments Regions of Land that do not contain significant amount of salt.
* Relevant information that can be used as input by Oil company analysts to assist them in making effective decisions.

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