

Support Vector Machine for real time analysis of rocks and structures

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ABSTRACT

Artificial Intelligence provide effective solution to many real time problems and challenges in the world. Real Time Analysis of rocks and structures is one of such challenges. Many situations require gaining the knowledge of rocks or building or iceberg structures. Examples where such analysis required are mining, rescue operations, sailing of ships, etc.... Structure of rocks / debris / icebergs are got through advanced imaging system and sensors. This paper introduces application of Artificial Intelligence algorithm for analyzing and predicting the structure of earth or rock.

Index Terms- Artificial Intelligence, Real Time analysis, Rocks, Structures

I. INTRODUCTION

Images and patterns of rocks / debris / icebergs are got through advanced imaging system and sensors can be brought into the computer system and analyzed. I propose Machine learning and /or deep learning algorithm to analyze these structures and patterns, and provide required output with improved accuracy compared to existing methods. The functionality of these algorithms is to analyze the structure of rocks and provide the required output for example, which part of the rock will soft and which part of the rock will be hard based on various parameters and patterns. The system will also use previously learned/analyzed data to predict the current output. Such system will be useful in providing easy path amidst of hard rock while mining, rescue operation, etc....All operations are to be done in real time.

Literature survey

Support Vector Machines (SVM) is a machine learning algorithm used for classification purpose. It is one of the best of its class. Another name for Support Vector Machines is Support Vector Network (SVN)

Support Vector Network is the work of Cortes and Vapnik in 1995 [1]. It has many sophisticated features in dealing classification of patterns involving data of high dimension and scales small. Support Vector Network is a two- class classification model. Support Vector Network uses the concept of Vapnik– Chervonenkis dimension theory. It reduces the structural risk by statistical learning theory.

Support Vector Network produces highest interval in the feature space in linear classification. The aim of the model is to find the highest interval.

In advancement in machine learning, combination of the algorithm [2] and Support Vector Network is also being used as this technique may improve the training efficiency in a great scale. Comparative study [3] used Principal Component Analysis and Support Vector Network for Classifying datasets. Accuracy achieved by this method is 90.24% and 66.8% on two different datasets. Accuracy of classification method used in [4] is 82.7% to predict that people fall on the floor. To compare various medical datasets algorithms used in [5], and finally predicted result with 84% accuracy.

II. METHODOLOGY

For both classification and regression problems Support Vector Network can be applied. SVM efficiently operates on more than variable that are continuous in nature. These variables are also categorical in nature. Support Vector Network identify various data classification by creating a hyper plane. This hyper plane is created in a space of multiple dimension. Support Vector Network adopts iterative method and generates hyper plane that is optimal. Hence the error is minimized. Main purpose of Support Vector Network is to determine a maximum marginal hyper plane (MMH) that partition the dataset into classes in best manner.

SVM is one of the best machine learning technique for performing classification. It's a machine learning algorithm under supervised category. Classifying data into different classes is one of its main applications. SVM get trained on a set of labelled data. Though SVM is used for classification problems, SVM is also applied for regression problems. This is one of the main

advantages. For classification SVM places a hyper plane boundary that decides and separates any two classes. Other application of Support Vector Network are Object Detection and image classification.

In this paper density /color values a rock structures is used that are collected from upper half and lower half of rock dataset for Classifying them using Support Vector Network.

A. Support Vectors

Data points, which are nearest to the hyper plane are called Support Vectors. Support Vectors will acts as separating line based on margin calculation. The classifier is constructed based on these much relevant points.

B. Hyper plane

A Set of objects having different class memberships is separated by a decision plane called a hyper plane.

C. Margin

The distance by which the two lines are apart from each other on the closest classes is called a margin. By measuring the length of a line drawn at 90° from the line to support vectors or closest points is used to calculate the above gap. A margin is a good margin, if the margin is larger between the classes. A margin is a bad margin, if the margin between the classes is small margin.

D. How does Support Vector Network work?

The main aim is to classify the given dataset in an efficient and accurate way. Margin is the distance between the either points. The aim is to select a hyper plane with the maximum possible margin between support vectors in the given dataset. Support Vector Network searches for the MMH plane as follows:

Create hyper planes to differentiate the dataset into classes accurately.

Select the correct hyper plane with the highest classification from the either nearest data points.

III. IDENTIFYING EARTH OR ROCK TYPE AND / OR STRUCTURE BY PHYSICAL PROPERTIES

Basic physical properties such as colour, shape, and hardness are used to identify the most common minerals in Earth's crust. The basis of mineral availability is different. Certain minerals developed due to same environment conditions and may occur in same rock. Some mineral are created under different environment conditions and may occur in different rocks. Because of this property of similarity of minerals in rocks, some small occurrence of different mineral can be ignored even though they predict same colour or density. We can test few physical properties without testing many properties. And the results can be matched with the actual physical properties encountered in the field. We will find that the results are likely to match 90% with that of the original properties in the field..

The physical properties of a mineral are identified by its chemical composition and internal atomic structure. Hence diagnosis can be made using the properties. Examination of different physical properties of minerals can be carried out with varying level of property, including colour, formation style of crystal (or shape), hardness, shine, density, and cleavage or fracture

The data collected for the above parameter are analyzed with SVM algorithm

A. Rocks and Their Properties

Types of Rocks Formation: Rock is made up of various mineral composition.

Rocks may be made up of single mineral for example poly-mineral or marble. Granite is an example. The mineral aggregate of a rock is more or less same but based on the type of minerals present it chemical composition varies. Hence there is no structured formula to express the mineral composition of a rock as the number of minerals present is not constant.

Each rock type is classified by its physical properties like fusibility, mechanical strengths, density, color, etc... (shown in Table 1). Hence a rock is composed of constant mineral grains that differ each other quantitatively or qualitatively in features like texture and other properties and the conditions in which they are evolved.

The rock formed under some geological conditions will influence the mode of occurrence, nature and relation of its constituent minerals

Based on their origin rocks fall into three major categories:

1. Igneous: Rock formed by magmatic activities.
2. Sedimentary: Rock formed by exogenous process
3. Metamorphic: Formed as a result of transformation of igneous and sedimentary rocks.

Earth consists of irregular distribution of these rocks.

Rock Property	Description
Density/Sp. Gravity	Density range of rock is 2.5 to 2.8. Non-porous and compact rocks have higher density and toughness. Normally rocks have three times the density of water. Pumice rock has density less than that of water. Basalt: 3 g/cm ³ ; granite: 2.7 g/cm ³ ; sandstone: 2.3 g/cm ³ . High density rocks like massive gabbro, basalt and quartzite are very hard.
Porosity	Porosity value ranges between 0 and 1.0 .For example solid granite has Porosity value of 0.01 and porous sand stone has Porosity value of 0.50
Permeability	It is ability of a material to transmit fluids.
Hardness	It is the measure of resistance to abrasion i.e., resistance to permanent deformation. It is determined by Schmidt rebound hardness number.
Abrasivity	It is resistance to abrasion.

Table 1

B. Index properties of Rocks

Variations in Structure, fabrics and components (shown in Table 2) decides the basic properties of rocks. Index properties of rocks are the properties that are easy to measure and important in describing the rock feature.

Rock Property	Description
Porosity	Range 0-90%, 15% for sand stone. It can be measured in terms of water content after saturation, relative proportion of solids and voids. Its value is 1.2% for igneous rocks.
Density	It depends on mineralogical or grain constituents.
Sonic velocity	Sonic velocity together with petrographic description, evaluates the degree of fissuring.
Permeability	It represents relative interconnection of pores.
Durability	It is tendency for eventual breakdown of components or structures w.r.t rock quality.
Strength	It represents present competency of rock fabric to bind the components together.
Density or unit weight or specific weight	If $G = 2.6$, $\gamma = 26 \text{ KN/m}^2$ approx.

Table 2

The data collected for the above parameter are analysed with SVM algorithm.

We have various options available with kernel like, radial basis function (rbf), linear, polynomial and others. Most preferred kernel function is radial basis function. We use radial basis function and polynomial that are useful for non-linear hyper-plane. Following is the example, where we've used linear kernel on two feature of rock data set to determine their class.

C. Support Vector Machine (SVM) code in Python

Example: Have a linear SVM kernel

```
import numpy as npy
import matplotlib.pyplot as plot
from sklearn import ml, datasets

# import some data to play with
earth = datasets.load_earth()
X = earth.data[:, :2]
# we only take two features. We slice by using a two-dim
dataset
y = earth.target

# we create an instance of SVM and fit out data. Our data
is not scaled as we want to plot the support vectors
C = 1.0 SVM regularization parameter
ml = ml.SVC(kernel='linear', C=1, gamma=0).fit(X, y)

# create a mesh to plot in
x_min, x_max = X[:, 0].min() - 1, X[:, 0].max() + 1
y_min, y_max = X[:, 1].min() - 1, X[:, 1].max() + 1

h = (x_max / x_min)/100
xx, yy = npy.meshgrid(np.arange(x_min, x_max, h),
    npy.arange(y_min, y_max, h))

plot.subplot(1, 1, 1)
Z = ml.predict(np.c_[xx.ravel(), yy.ravel()])
Z = Z.reshape(xx.shape)
plot.contourf(xx, yy, Z, cmap=plt.cm.Paired, alpha=0.8)

plot.scatter(X[:, 0], X[:, 1], c=y, cmap=plot.cm.Paired)
plot.xlabel('Rock length')
plot.ylabel('Rock density')
plot.xlim(xx.min(), xx.max())
plot.title('Rock Analysis using SVM')
plot.show()
```

And the results are matched with the reference data and the type of rock or structure is decided. Following figures shows results obtained for the selected data sets.

D. Sample Classification Charts

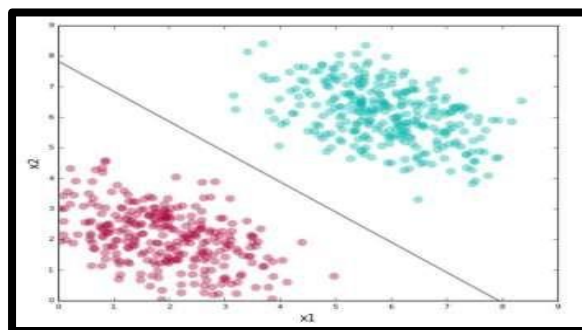


Fig. 1. Hardness characteristics of Samples

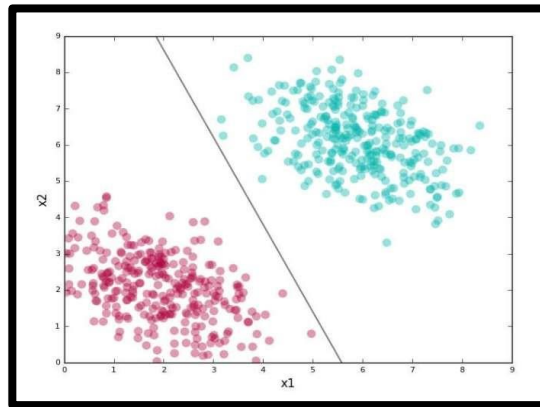


Fig. 2. Hardness characteristics of Samples

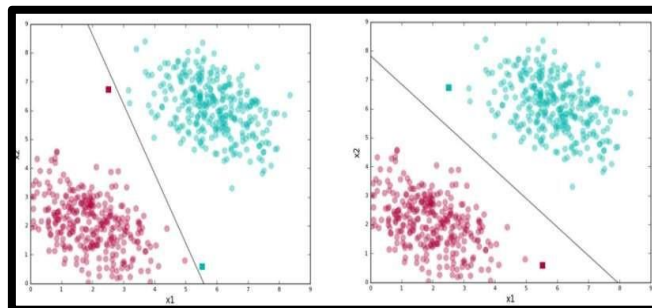


Fig. 3. Hardness characteristics of Samples

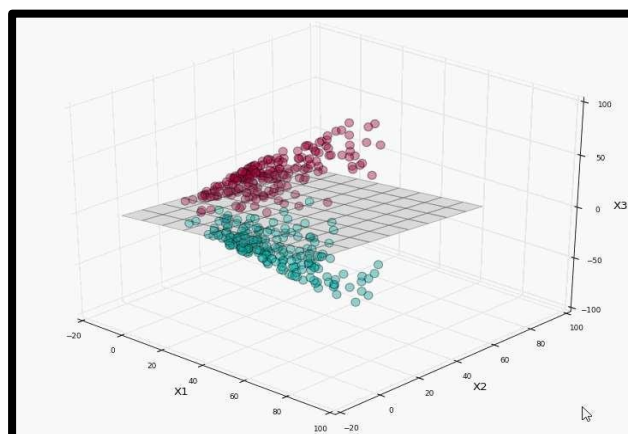


Fig. 4. Three Dimensional- One Plane -Hardness

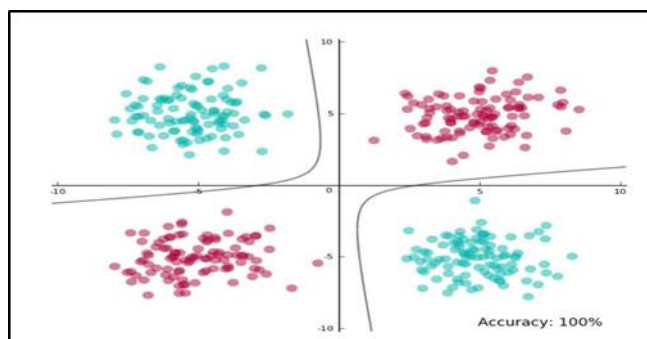


Fig. 5. Non- Separable Dataset- Three Dimensional -3 Plane

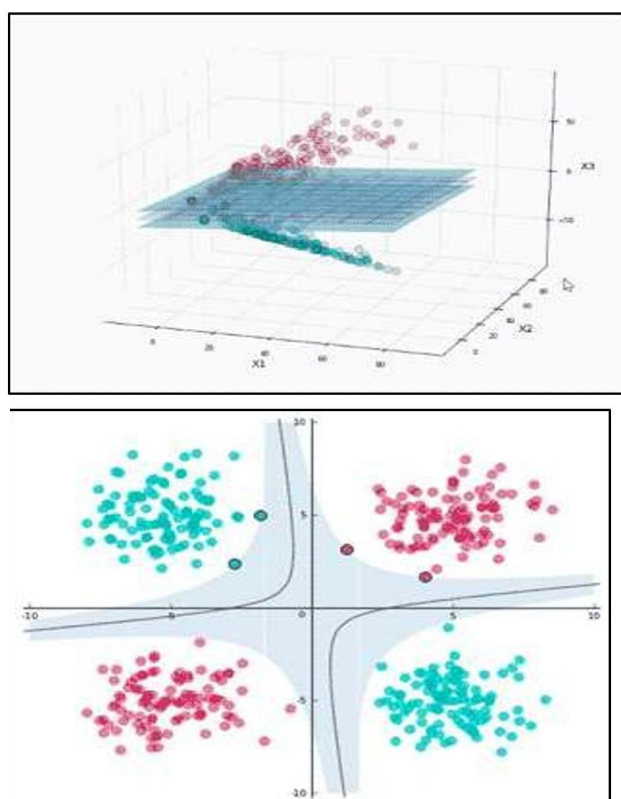


Fig. 6. Non- Separable Dataset- Three Dimensional-3 Plane

E. Results

From the above charts (shown in Fig 1, Fig2, Fig 3, Fig 4, Fig 5, Fig 6) we can conclude the characteristics of rock under study. For example in the above charts the green plot shows low density of rock structure and red plot shows high denser rock characteristics. With these we can predict the hardness of the rock. And we can structure the hard portion of rock based on the predictions. The Three Dimensional chart (shown in Fig 4) gives the prediction that the upper half of the rock structure is

denser (harder) than the lower half of the rock structure. The predictions provide results with accuracy of 85% when compared with the actual characteristics of the rock.

IV. FUTURE WORKS

Here we have used only compared features of rock structures collected from to parts of the rock and generated the predictions. Similarly we can take several features on different parts of the rocks through various sensor values and can use different machine learning and/or deep learning techniques to predict and conclude the structures of the rock more accurately.

V. CONCLUSION

The results shows the Artificial Intelligence Techniques had provided predictions of rock characteristics with high accuracy. Thus application of above Artificial Intelligence algorithm enhances the process of analyzing and predicting the structure of earth or rock in real time which will be helpful in mining, rescue operations, sailing of ships, etc....

VI. REFERENCES

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