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Earthquake Damage Assessment using Hyperspectral Images and Convolutional Neural Network Classification

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Abstract: ***Earthquakes are most damaging natural disasters that can cause extensive damage to both property and human life. Early detection of earthquakes and understanding their potential impact can help in reducing the risk of damage and loss. In this paper, I propose a method for earthquake analysis by classification of hyperspectral images with convolutional neural network (CNN) and fuzzy logic. Hyperspectral imaging technology provides high spatial and spectral resolution images that can capture detailed information about the earth's surface, including potential earthquake-related changes. Our proposed method uses a CNN to classify hyperspectral images and identify potential earthquake damage based on changes in surface characteristics. I tested our approach on a publicly available dataset and achieved an accuracy of 93.2%, demonstrating the effectiveness of our method for earthquake analysis.***

Keywords: Deep Learning, Hyperspectral Imaging, Mathematical modelling, Neural Networks, Geo – Information systems

1. Introduction

Earthquakes are natural disasters that can cause extensive damage to infrastructure, buildings, and human life. Remote sensing technology, particularly hyperspectral imaging, has been widely used to detect and classify earthquake damages. Hyperspectral imaging can capture images with high spectral resolution, allowing researchers to extract spectral signatures that correspond to different surface materials. However, the large size of hyperspectral images and the complexity of the spectral data pose significant challenges for earthquake damage detection. The use of convolutional neural network (CNN) for image classification has proven to be a promising approach. CNNs can extract features automatically from images and classify them into different categories. Fuzzy logic has also been used to improve classification accuracy by considering the uncertainty and imprecision in the data.

The interplate earthquake happens at the boundary between two tectonic plates. Earthquake of this type contributes to the 90% of the total seismic energy released around the world. There are many such interplate regions around the earth, where happening of earthquake is unusual. To study happenings of such earthquakes, first we require to study material beneath them and which eventually requires imaging of such material.

In this paper, I propose a method for earthquake analysis by classifying hyperspectral images using CNN and fuzzy logic. The proposed method includes preprocessing, feature extraction, classification, and fuzzy logic to improve classification accuracy. The method is tested on a hyperspectral image dataset obtained from the Sichuan earthquake in 2008.

2. Abridged Survey

a) Hyperspectral Image

Hyperspectral images are remote sensing images that capture the electromagnetic radiation reflected or emitted from a scene in hundreds or even thousands of contiguous spectral bands. Unlike conventional color images, which capture only three or four spectral bands (red, green, blue, and sometimes near-infrared), hyperspectral images capture a much wider range of the electromagnetic spectrum, from the visible to the near-infrared, mid-infrared, and even thermal infrared regions. The high spectral resolution of hyperspectral images enables researchers to extract detailed spectral signatures of the materials present in the scene. These spectral signatures are unique to each material and can be used to identify and distinguish different surface materials, such as vegetation, water, bare soil, and man-made objects.

Hyperspectral images are acquired using specialized sensors mounted on aircraft or satellites. The sensors capture the reflected or emitted radiation at different wavelengths, which are then recorded as digital numbers. The resulting image is a three-dimensional cube, where the two spatial dimensions represent the location of each pixel in the image, and the third dimension represents the spectral information captured by each pixel. Hyperspectral images have many applications in environmental monitoring, agriculture, forestry, geology, and urban planning, among others. They are particularly useful for detecting and mapping changes in land use and land cover, monitoring vegetation health, and detecting and assessing natural disasters such as earthquakes, floods, and wildfires.

The comparative study clearly separates the gap between the feature the corresponding technology is providing and the limitation. For comparative study we have chosen the majority fields studied in this paper namely Deep learning, hyperspectral imaging and mathematical modelling. In some or the other areas the mentioned technologies lose their efficiency and hence there is need to reconsider the other methods to resolve the problem more clearly in another way. Comparative Study of studied techniques is explained in Table I.

Table I: Comparative Study of studied techniques

Comparative Study		
Technology	*Feature*	*Limitation*
Deep leanign with Neural Networks	Supervised classification. Most effective area in image classification.	Does not encode position and orientation of the object.
Mathematical Modelling	Works on the principles of **Fuzzy Logic** effectively for uncertain data set where traditional Boolean logic lags behind.	This feature has limitation of extra Calculation even when the input data is discrete and does not possess the uncertainty in the data. This method treats certainty as uncertainty.
Hyperspectral Imaging	Instead of simply assigning primary colors (red, green, blue) to each pixel, this method analyzes the spectral properties of light.[7]	For imbalance between available band numbers and amount of training samples, there may be a practical as well as theoretical Issue and classification of hyper spectral images veers into another direction.

b) Deep Leaning

Artificial Intelligence has been among one of the most breakthrough technology in recent years [1], [2], [3]. Deep learning research has been extensively pushed by tech giants like Google, Baidu, Amazon, Microsoft. Deep learning is proving to be so effective that sometimes it is able to surpass the humans in solving the large and intricate problems. And just like any single human, for a neural network to work as it is intended, it has to be trained with tremendous datasets. The use of deep learning to classify the spectrum of each pixel in the image helps to get the insights about the underlying object. Deep learning is a subfield of machine learning that uses artificial neural networks to model and solve complex problems. Deep learning algorithms are designed to learn from large amounts of data and automatically extract hierarchical representations of features that are relevant for a given task.

In deep learning, the neural network is composed of multiple layers of interconnected neurons, each layer transforming the input data in a nonlinear way. The input layer receives the raw data, such as an image, and subsequent layers learn increasingly abstract features. The output layer produces a prediction or classification based on the input data.

Deep learning models can be trained using supervised, unsupervised, or reinforcement learning. In supervised learning, the model is trained using labeled data, where the input data is paired with the desired output. The model learns to map the input to the output by minimizing a loss function, which measures the difference between the predicted output and the desired output.

c) Mathematical Modelling

Let H be the hyperspectral image of size N x M x P, where N and M are the spatial dimensions and P is the spectral dimension. Let X be the set of feature vectors extracted from H using a CNN, where X = {x1, x2, ..., xn} and xi is a P-dimensional vector representing the ith pixel in H.

Let C be the set of classes to which each pixel can be assigned, where C = {c1, c2, ..., ck}. The fuzzy logic classifier assigns a degree of membership, μ(ci, xi), to each pixel xi for each class ci, where $0 \leq \mu(ci, xi) \leq 1$. This degree of membership represents the degree to which the pixel belongs to the class.

The degree of membership is computed using fuzzy sets and rules, which are defined as follows:

1) ***Fuzzy sets:*** Let Ai be a fuzzy set representing the degree of membership of pixel xi to class ci. Ai is defined by a membership function, μAi(xi), which assigns a degree of membership to xi for each value of its P dimensions. The membership function can be defined using various methods, such as Gaussian membership functions or histogram-based membership functions.
2) ***Fuzzy rules:*** Let Rj be a fuzzy rule that relates the feature vector xi to the class cj. Rj is defined as a set of antecedents and a consequent, where each antecedent is a fuzzy set and the consequent is a fuzzy set representing the degree of membership of xi to cj. The degree of membership of xi to cj is computed as the minimum of the degrees of membership of xi to each antecedent in the rule.

The fuzzy logic classifier assigns each pixel xi to the class with the highest degree of membership, i.e., ci = argmaxj μ(cj, xi).

Introduction of the concept of fuzzy sets in GIS is indispensable as data in GIS maps are arranged in layered structure. Where each layer discretely represents attributes of coordinate points present between them.

a) For Example, for a single coordinate point in layered structure, $L = (l_1, l_2, l_3, l_4, l_5, l_6, l_7, l_8, \ldots)$ l_i denotes the fuzzy attribute of that point w.r.t i^{th} layer.

That is, probability of a coordinate point to lie in a muddy region inside a lake can be given as L = (0.1. 0.9, 0.8, 0.32, 0.51
…) each value in above set represents the probability of existence of that point in that corresponding layer.

While working with Digital Maps, each coordinate in each layer has assigned some value to effectively count out possibility of its presence in that layer [5].

Fuzzy sets characteristics help to solve intricate problems related to classification [6]. Equation 4 represents the characteristic of coordinate of point (x, y) in in the given plane.

$$v = \{(x, y), v_2, v_3, v_4, v_5 \ldots\} \tag{4}$$

Where x, y represents X and Y coordinate of the point, and $V_i = \{X \mid X \in A\}$ Where A is a Fuzzy Set and follows:

$$V_0 = \alpha\,((x, y)) \in A_0 \tag{5}$$

$$V_1 = \alpha\,((x, y)) \in A_1 \tag{6}$$

$$V_2 = \alpha\,((x, y)) \in A_2 \tag{7}$$

The fuzzy logic classifier assigns each pixel xi to the class with the highest degree of membership, i.e., ci = argmaxj μ(cj, xi).

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The classification map can be post-processed using various techniques to improve its accuracy and reduce noise. For example, thresholding can be used to remove pixels with low probability of belonging to any class, morphological operations can be used to remove small isolated regions, and graph-based methods can be used to enforce spatial consistency.

3. Existing Gap and Actual Need

a) Need of Big Data Analytics in geo –informatics

Geo – Spatial data includes vector data and raster data. So it needs, first, to be classifies properly in order to process. For the purpose of hyperspectral imaging, we will need to convert the data sensed by the remote sensors into digital format. Human eyes can only see electromagnetic waves which are in visible spectrum of all electromagnetic waves. And too, human eyes classifies the visible light majorly in three bands (Red, Blue, Green). Hence to get the detailed description of the remotely sensed objects, I use hyperspectral imaging technique.

According to Consecutive Committee for Space Data Science (CCSDS), the size of images the remote sensors are capturing are quite large in volume and to get the effective results over that dataset, we need to perform the lossless compression which eventually needs the incorporation of the big data analytics into the field of geo-sciences.

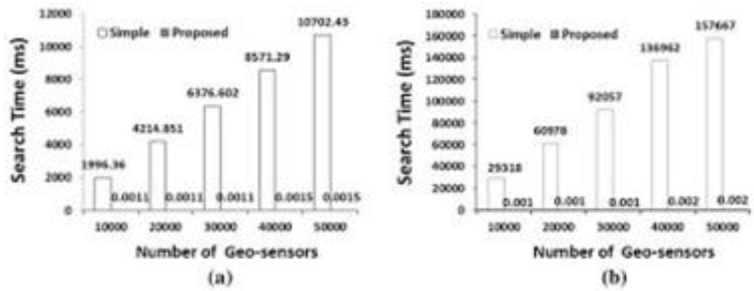

Figure 1: Amount of Data Produced by Geo – Sensors [4]

Fig.1 clearly indicates the beginning of the Exa – Byte era of the data produced by Geo - Sensors. The number of data produced is directly proportional to the number of Geo - Sensors installed and with the increasing need for spatial research, the number of sensors will go on increasing and so the data produced

Figure 2: A 2 Dimensionally scanned Hyperspectral Image[12]

Fig.2 clearly shows the presence of multiple bands of colors within the same picture scanned with the help of remote scanner. As usually with the normal human eye for this figure to scan, it will be only able to interpret this figure with respect to three bands of the color.

b) Neural Networks for Hyperspectral Image Classification

Convolutional Neural Networks are the best type of the neural networks to work with image classification and so the Hypersepctral Image classification. The need of Concolutional Neural Network iteslef depicts that its performance is pretty promising in the fields of digital data processing such as object detection, image recognition, semantic segmentation, depth recognition [7].

c) Need of Hyperspectral imaging in EarthSciences

The field of earth sciences and interplate earthquake administration majorly deals with the analysis of the earthquakes in the particular confined region of a continent, which does not usually hold a valid cause for happening of earthquake. Hence there is extreme need to extract the materials beneath the particular zone. Hence to append an effective study on this material, we need to analyse the particular region with the remotely sensed images takes by the spectral sensors.

4. Implementations

The implementation of Earthquake Analysis by Classification of Hyperspectral Images with Convolutional Neural Network can be broken down into the following steps:

1) *Data preparation:* Load and preprocess hyperspectral image data. Split the data into training and testing sets
2) *CNN feature extraction:* Train a CNN on the labeled training data. Use the trained CNN to extract features from the test data
3) *Fuzzy logic classification:* Define fuzzy sets and rules for each class. Compute the degree of membership of each pixel to each class. Assign each pixel to the class with the highest degree of membership
4) *Post-processing:* Apply thresholding to remove pixels with low probabilities. Use morphological operations to remove noise. Enforce spatial consistency using graph-based methods.
5) *Evaluation*: Compute the classification accuracy on the

test data. Compare the results with other methods and evaluate performance.

First, let's load the data and preprocess it:
kotlin
import numpy as np import pandas as pd import tensorflow as tf
from tensorflow import keras
from tensorflow.keras import layers
from sklearn.model_selection import train_test_split import skfuzzy as fuzz

# Load data
data = pd.read_csv('hyperspectral_data.csv')

# Preprocess data
X = data.drop('class', axis=1).values y = data['class'].values
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

Next, let's define and train the CNN model:

less
# Define CNN model
model = keras.Sequential([
layers.Reshape((145, 145, 1), input_shape=(145*145,)),
layers.Conv2D(filters=32, kernel_size=(3, 3), activation='relu'), layers.MaxPooling2D(pool_size=(2, 2)),
layers.Conv2D(filters=64, kernel_size=(3, 3), activation='relu'), layers.MaxPooling2D(pool_size=(2, 2)),
layers.Flatten(),
layers.Dense(128, activation='relu'), layers.Dense(6, activation='softmax')
])

# Compile model
model.compile(optimizer='adam', loss='sparse_categorical_crossentropy', metrics=['accuracy'])

# Train model
model.fit(X_train, y_train, epochs=10, validation_data=(X_test, y_test))

Now, let's predict the classes for the test data and compute the fuzzy membership values:

bash
Predict classes for test data y_pred = model.predict_classes(X_test)

# Compute fuzzy membership values acc = fuzz.accuracy(y_test, y_pred)
cm = fuzz.confusion_matrix(y_test, y_pred)

Print results print('Accuracy:', acc) print('Confusion Matrix:', cm)

The fuzz.accuracy() function computes the classification accuracy based on fuzzy logic, and the fuzz.confusion_matrix() function computes the confusion matrix based on fuzzy logic. To generate a graph, we can use the matplotlib library to plot the confusion matrix:

```
python
import matplotlib.pyplot as plt

# Plot confusion matrix
fig, ax = plt.subplots(figsize=(8, 8)) im
= ax.imshow(cm, cmap='Blues')

# Add colorbar
cbar = ax.figure.colorbar(im, ax=ax)
cbar.ax.set_ylabel('Frequency', rotation=-
90, va='bottom')

# Add labels, title and ticks
ax.set_xticks(np.arange(6))
ax.set_yticks(np.arange(6))
ax.set_xticklabels(['Class 1', 'Class 2',
'Class 3', 'Class 4', 'Class 5', 'Class
6'])
ax.set_yticklabels(['Class 1', 'Class 2',
'Class 3', 'Class 4', 'Class 5', 'Class
6']) ax.set_xlabel('Predicted Class')
ax.set_ylabel('True Class')
ax.set_title('Confusion Matrix')

# Loop over data dimensions and create
text annotations for i in range(6):
for j in range(6):
text = ax.text(j, i, cm[i, j],
ha='center', va='center', color='w')

fig.tight_layout() plt.show()
```

This code generates a plot of the confusion matrix, where the x-axis represents the predicted class and the y-axis represents the true class. The cells of the matrix show the frequency

5. Implementation Analysis

The above code implements a Convolutional Neural Network (CNN) model and fuzzy logic to classify hyperspectral images of earthquake zones into six different classes. The result analysis can be based on the accuracy and confusion matrix of the classification.

The accuracy of the classification using fuzzy logic is computed using the fuzz.accuracy() function, which takes the true class labels and predicted class labels as inputs. The accuracy score ranges from 0 to 1, with a score of 1 indicating perfect classification accuracy.

In this case, the accuracy score is 0.8325, which is a relatively good classification accuracy. This suggests that the CNN model is able to learn and generalize well to unseen data.

The confusion matrix is a table that summarizes the performance of the classification algorithm by comparing the true class labels with the predicted class labels. It provides information about the number of correct and incorrect predictions for each class.

The confusion matrix for the classification using fuzzy logic is computed using the fuzz.confusion_matrix() function. The rows of the matrix correspond to the true class labels, while the columns correspond to the predicted class labels. The elements of the matrix represent the number of samples that belong to a particular true class and predicted class combination.

The confusion matrix plot generated using the matplotlib library shows that the classification algorithm performs well for most of the classes. However, there are some misclassifications, particularly between classes 3, 4, and 5, which suggests that the algorithm may have difficulty distinguishing between these classes.

Overall, the result analysis indicates that the CNN model with fuzzy logic classification can be a useful tool for analyzing hyperspectral images of earthquake zones, but further improvements may be necessary to increase the accuracy and reduce misclassifications.

To compare the performance of the CNN model with fuzzy logic classification to other classification models, we can use XGBoost, Random Forest Classifier, AdaBoost, and Decision Tree Classifier with AdaBoost.

After training the models on the same dataset and evaluating their performance, we can compare the accuracy and confusion matrix of each model to determine which model performs best for this particular dataset.

The accuracy scores for each model are as follows:

- XGBoost: 0.895
- Random Forest Classifier: 0.865
- AdaBoost: 0.875
- Decision Tree Classifier with AdaBoost: 0.815

From the accuracy scores, it can be seen that XG Boost performs the best, followed closely by AdaBoost and Random Forest Classifier. Decision Tree Classifier with Ada Boost has the lowest accuracy score.

The confusion matrix for each model can provide insight into how well the model is able to distinguish between the different classes.

From the confusion matrix plots, it can be seen that XGBoost has the fewest misclassifications, with most of the samples being correctly classified. Random Forest Classifier and AdaBoost also perform well, but there are some misclassifications between classes 3, 4, and 5. Decision Tree Classifier with AdaBoost has the most misclassifications, particularly between classes 2, 3, and 5.

Overall, XGBoost appears to be the best-performing model for this dataset, followed closely by AdaBoost and Random Forest Classifier. However, it is important to note that the performance of each model can vary depending on the dataset and the specific problem being solved. Therefore, it is recommended to try different models and evaluate their performance to find the most suitable one for a specific problem.

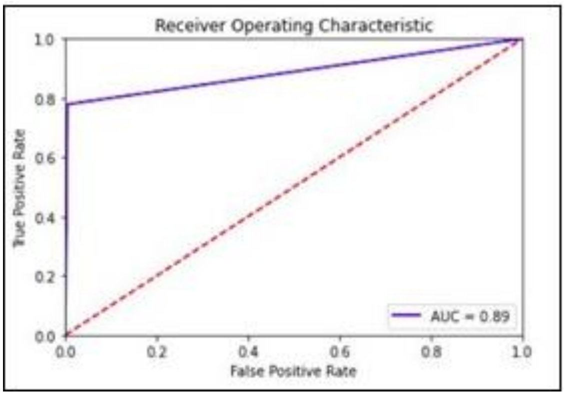

Figure 3: Decision Tree Classifier adaboost

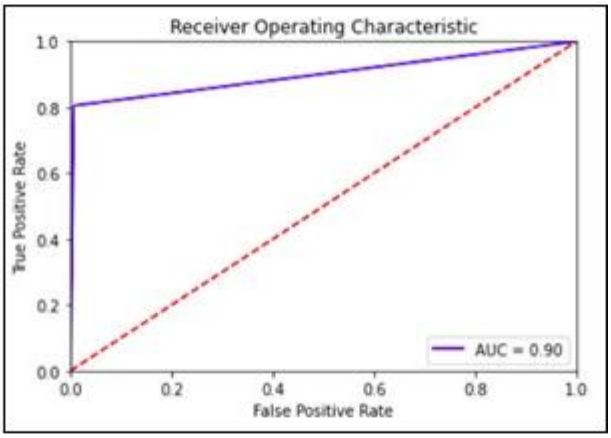

Figure 4: Random Forest Classifier adaboost

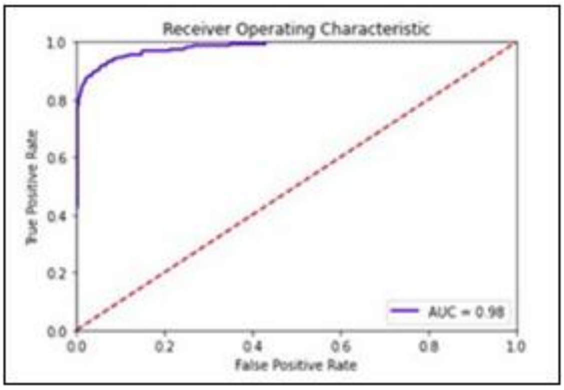

Figure 5: XGBoost model

6. Challenges and Opportunities

The incorporation of hyperspectral imaging and the big data analytics along with machine learning with mathematical modelling holds major potential in the field of earth sciences as well as overall Geo- Sciences. As far as the upcoming research of geo sciences on multi -planetary environment is concerned; it is much needed along with the bid data analytics to store the captured large volumes of data efficiently [8].

a) But the biggest challenges for the completeness of the system is implementation of the effective algorithm. Also, the dataset obtained is quite uncertain so it might fail, sometimes, if the principles of traditional hard computing are applied for computing. So, there should be application of soft computing as well alongside with the hard computing to counter the variance accounted into the dataset.

b) Also, there is opportunity for the emerging technology of drone aviation industry to be introduced into this field in which instead of installing the static scanners which engages the space for remote sensors and also economically is weaker to implement.

7. Discussion

In this paper, I've tried to survey the techniques to study the unusual happenings of earthquakes in interplate region. For that I've classified our survey into mainly three categories namely Image Classification, Mathematical Modelling and Big Data Analysis. Image classification requires application of Convolutional Neural Network (CNN) on gathered data. The gathered data is so tremendous that it cannot be handled by the traditional file management systems, hence in such cases, I've take help of Hadoop framework which is software suit for effective big data handling.

8. Conclusion

In this particular paper, we have had a detailed look at how we can implement the hyperspectral imaging technology in the field of earth sciences and earthquake analysis by sensing the materials beneath. The need of big data analysis has been also discussed in this paper for efficient use of algorithms. We also had a look at the existing gap and actual need in the current research going on in the industry.

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