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Disaster Intensity Based Selection of Training samples for Remote Sensing Building Damage Classification

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Abstract- Previous applications of machine learning in remote sensing for the identification of damaged buildings in the aftermath of a large-scale disaster have been successful. However, standard methods do not consider the complexity and costs of compiling a training data set after a large-scale disaster. In this Project, study disaster events in which the intensity can be modeled via numerical simulation and/or instrumentation. For such cases, two fully automatic procedures for the detection of severely damaged buildings are introduced. The fundamental assumption is that samples that are located in areas with low disaster intensity mainly represent non damaged buildings. Furthermore, areas with moderate to strong disaster intensities likely contain damaged and non damaged buildings. Under this assumption, a procedure that is based on the automatic selection of training samples for learning and calibrating the standard support vector machine classifier is utilized. The second procedure is based on the use of two regularization parameters to define the support vectors. These frameworks avoid the collection of labeled building samples via field surveys and/or visual inspection of optical images, which requires a significant amount of
time.

Keywords— Building, Disaster, Support vector machine, parameters, calibration.

I. INTRODUCTION

Machine learning has become a dominant data processing paradigm for the extraction of information from remote sensing data. The underlying strategy is to establish a model from limited but properly encoded prior knowledge (i.e., training samples) to assign a thematic label (e.g., a damage state in the application context of this article) to an instance under analysis (e.g., a building). Such methods are especially useful if explicit modeling based on, e.g., mechanical models, is too complex. At the same time, such approaches require both a sufficient amount of prior knowledge and viable descriptors to characterize the instances under analysis in order to achieve high predictive accuracy. However, many applications suffer from the unavailability of a sufficient number of training samples. In numerous cases, gathering training samples can become immensely expensive and timeconsuming. Under these circumstances, various approaches have been proposed for alleviating the scarceness of training samples.

The necessary logistics for conducting a field survey directly after a major natural disaster and the subsequent digitization of the data are expensive and time-consuming. Furthermore, in most cases, avoidance of human exposure to hazardous areas is recommended. In the context of disaster mitigation, damage mapping is a race against the clock. The faster a satisfactory estimate is provided, the faster the first aid can be sent and the higher the chances that people who are trapped in collapsed buildings will survive . As described earlier, a critical issue of the application of machine learning for damage mapping using remote sensing data is the lack of training data. Among the potential solutions is the development of a global network by building upon crowdsourcing for rapid damage assessment. Another potential solution is to transfer training data that have been collected from one disaster event to another disaster event. To realize this objective, the database must be sufficiently large to consider various sensors, seasonal variations, various building types and infrastructural typologies, and heterogeneous types of disasters.

Furthermore, not all disasters are recorded by remote sensing data, and training data are available for even fewer events. There are, however, recent studies for a specific type of disaster There is, however, a substantial pitfall in relying on fragility functions: fragility functions are available only for limited types of disasters, such as earthquakes and tsunamis. There is also a controversy regarding the transferability of fragility functions that have been constructed from empirical data, for instance, whether fragility functions for wooden buildings that were constructed in Japan can be used in other countries. To establish a solution that is independent of the availability of fragility functions, we uniquely deploy the estimated demand parameter directly after a hazardous event for automatic rule-based training sample selection. The spatial distribution of the affected buildings is expected to be consistent with the spatial distribution of the demand parameter. Namely, areas that are assigned a low demand parameter should contain mainly nondamaged buildings. In contrast, areas with a medium and large demand parameter likely include buildings with different damage levels. Using these assumptions, our objective is to learn a model that can solve a dichotomous classification problem and distinguish between two thematic classes: “severely damaged buildings” and “nonseverely damaged buildings.” The most common approach, termed change detection, aims to identify changes between a pair of images recorded before and after a disaster, from which changed samples are associated with severely damaged buildings and nonchanged samples are associated with nonseverely damaged buildings. It is assumed that, given that the images’ recording time is close, the changes between the images are associated with the

effects of the disaster. We provide two novel methods for calibrating a support-vector machine- based discriminant function. As feature space, we use hand-engineered features computed from remote sensing data. The demand parameter is used to collect the training data automatically. Using automatic sample selection for change detection is not a new idea. Previous studies have first used unsupervised classification to collect reliable samples of changed and nonchanged samples and then improve the classifier using supervised/semisupervised classification algorithms. Unfortunately, such approaches to collect training samples do not provide a complete representation of the classes in the feature space. Furthermore, to the best of our knowledge, unsupervised techniques perform poorly when the disaster-affected area is much smaller than the area covered by the remote sensing data.

II. RELATEDWORKS

Previous applications of machine learning in remote sensing for the identification of damaged buildings in the aftermath of a large-scale disaster have been successful. However, standard methods do not consider the complexity and costs of compiling a training data set after a large-scale disaster. In the existing system, the system studies disaster events in which the intensity can be modeled via numerical simulation and/or instrumentation. For such cases, two fully automatic procedures for the detection of severely damaged buildings are introduced.

The fundamental assumption is that samples that are located in areas with low disaster intensity mainly represent non damaged buildings. Furthermore, areas with moderate to strong disaster intensities likely contain damaged and non damaged buildings. Under this assumption, a procedure that is based on the automatic selection of training samples for learning and calibrating the standard support vector machine classifier is utilized. The second procedure is based on the use of two regularization parameters to define the support vectors. These frameworks avoid the collection of labeled building samples via field surveys and/or visual inspection of optical images, which requires a significant amount of time.

Disadvantages of Existing system

In the existing work, the system did not implement Distance-Based Sample Selection (DSS) Approach. This system is less performance due to lack of machine learning methods.

1) Title: Multi objective-based sparse representation classifier for hyperspectral imagery using limited samples

Author: B. Pan, Z. Shi, and X. Xu,

Description: Recent studies about hyperspectral imagery (HSI) classification usually focus on extracting more representative features or combining joint spectral-spatial information. However, besides feature extraction, developing more powerful classifiers can also contribute to the accuracies of HSI classification. In this paper, propose a multiobjectivebased sparse representation classifier (MSRC) for HSI data, which mainly tries to address two problems: 1) pixel mixing and 2) lacking abundant labeled samples. MSRC is motivated by the SRC, and further integrating the idea of hyperspectral unmixing. Different from the traditional SRC-based methods, the novelty of MSRC consists of the optimization process, i.e., directly handle the L0-norm problem without any relaxation. The sparse term is not considered as a regularization operation. Instead, we transform the problem of weight vector estimation to subset selection, and propose a multiobjective-based method to optimize the L0-norm sparse problem. The residual term and sparse term are regarded as two parallel objective functions that are optimized simultaneously.

2) Title: Multitask Active Learning for Characterization of Built Environments With Multisensor Earth Observation Data

Author: C. Geiß, M. Thoma, M. Pittore, M. Wieland,

Description: propose a multitask active learning (AL) framework for an efficient characterization of buildings using features from multisensor earth observation data. Conventional AL methods establish query functions based on a preliminary trained learning machine to guide the selection of additional prior knowledge (i.e., labeled samples) for

model improvement with respect to a single target variable. In contrast to that, here, we follow three multitask AL metaprotocols to select unlabeled samples from a learning set which can be considered relevant with respect to multiple target variables. In particular, multitask AL methods based on multivariable criterion, alternating selection, rank combination, as well as hybrid approaches, which internalize multiple principles from the different metaprotocols, are introduced. Thereby, the alternating selection strategies implement a so-called one-sided selection (i.e., single-task AL selection for a reference target variable with simultaneous labeling of the residual target variables) with a changing leading variable in an iterative selection process. The multivariable criterion-based methods and rank combination approaches aim to select unlabeled samples based on combined single-task selection decisions. Experimental results are obtained from two application scenarios for the city of Cologne, Germany. Thereby, the target variables to be predicted comprise building material type, building occupancy, urban typology, building type, and roof type. Comparative model accuracy evaluations underline the capability of the introduced methods to provide superior solutions with respect to one-sided selection and random sampling strategies.

3) Title: Cost-sensitive multitask active learning for characterization of urban environments with remote sensing

Author: C. Geib, M. Thoma, and H. Taubenbock

Description: propose a novel cost-sensitive multitask active learning (CSMTAL) approach. Cost-sensitive active learning (CSAL) methods were recently introduced to specifically minimize labeling efforts emerging from ground surveys. Here, we build upon a CSAL method but compile a set of unlabeled samples from a learning set which can be considered relevant with respect to multiple target variables. To this purpose, a multitask meta-protocol based on alternating selection is implemented. It comprises a so-called onesided selection (i.e., single-task AL selection for a reference target variable with simultaneous labeling of the residual target variables) with a changing leading variable in an iterative selection process. Experimental results are obtained for the city of Cologne, Germany. The target variables to be predicted, using features from remote sensing and a support vector machine framework, are “building type” and “roof type.” Comparative model accuracy evaluations underline the capability of the CSMTAL method to provide beneficial solutions with respect to a random sampling strategy and noncost-sensitive multitask active sampling.

III. PROPOSED SYSTEM ARCHITECTURE

The Proposed System is as Follows:

1) The demand parameter allows reducing the search for changes to solely areas with medium/large demand parameters.

2) The system uses a threshold on the demand parameter to collect non changed samples. The demand parameter has a clear physical meaning, and thus, the selection of the demand threshold is very intuitive and does not require preliminary processing, such as unsupervised classification algorithms.

3) Because the demand parameter information is independent of remote sensing data, the collected non changed samples provide a better representation of the class non changed in the feature space.

4) The system integrates information from in-place sensors (i.e., ground motion sensor, tidal gauges), numerical simulation of a natural phenomenon, and remote sensing.

Advantages of Proposed system

The system is more effective since it presents Multiple Regularization Parameter (MRP) Approach.

The system is accurate since it is implemented Distance-Based Sample Selection (DSS) Approach.

There are two modules in the proposed system. They are :

1.Service Provider

In This Module The Functionalities are as follow:

➢ View Data Set Details
➢ Train Disaster intensity Data Set Details
➢ Train for Disaster prediction
➢ View all Disaster Details
➢ View Data Sets Tested details
➢ View all users
➢ View Disaster intensity Tested Results
➢ View Train & Test Results

2.User

In This Module The Functionalities are as follow:

➢ Post Data Sets
➢ Predict Disaster Intensity details
➢ View Your Profile

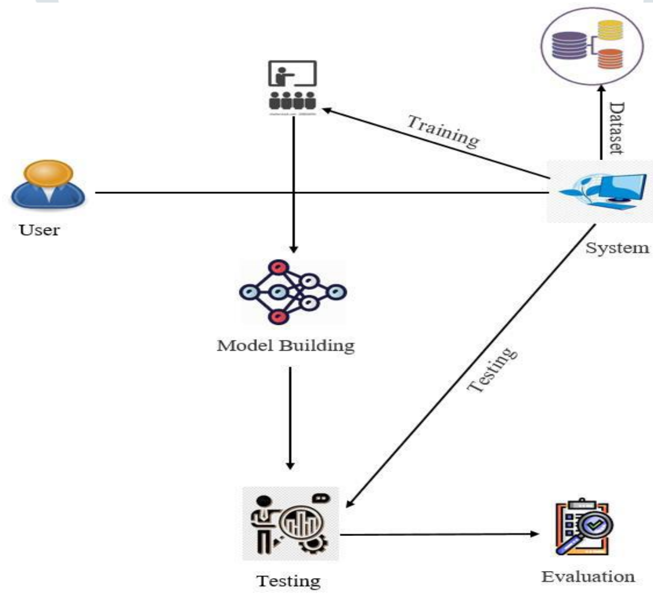


Fig.1 Architecture of proposed system

IV. RESULTS AND DISCUSSION

The output screens obtained after running and executing the system are shown from Fig.2 to Fig.8

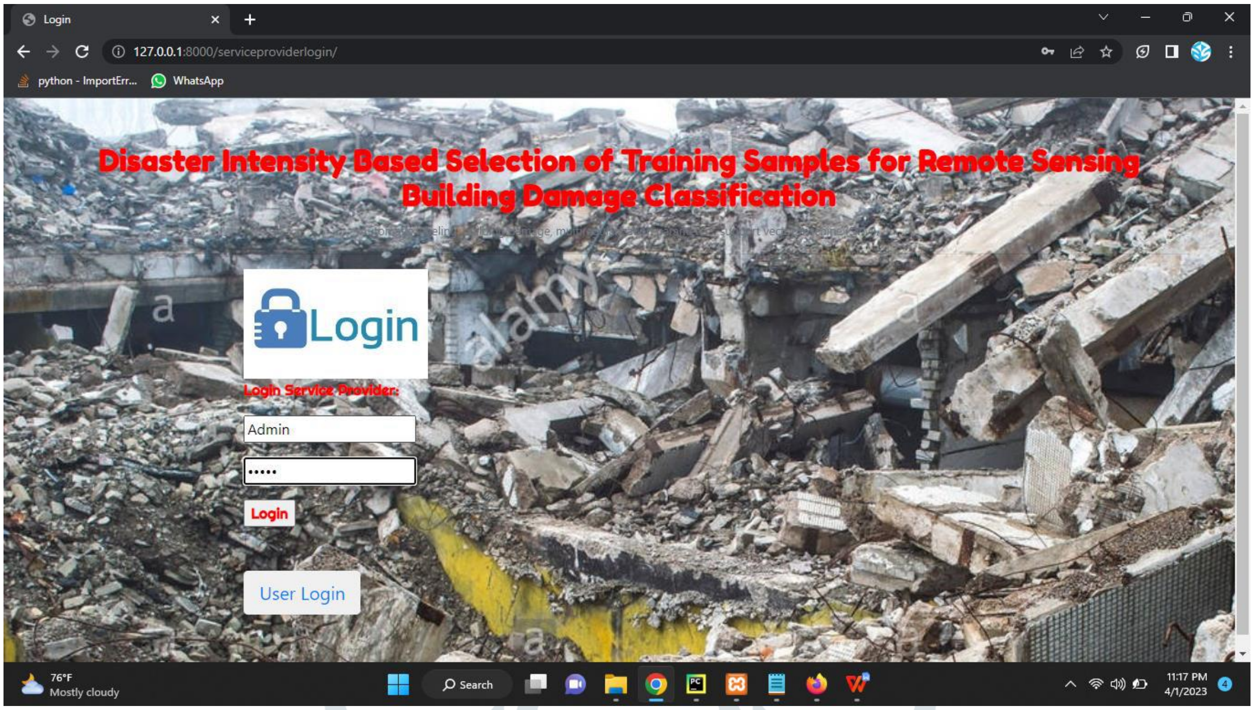


Fig.2 service provider login

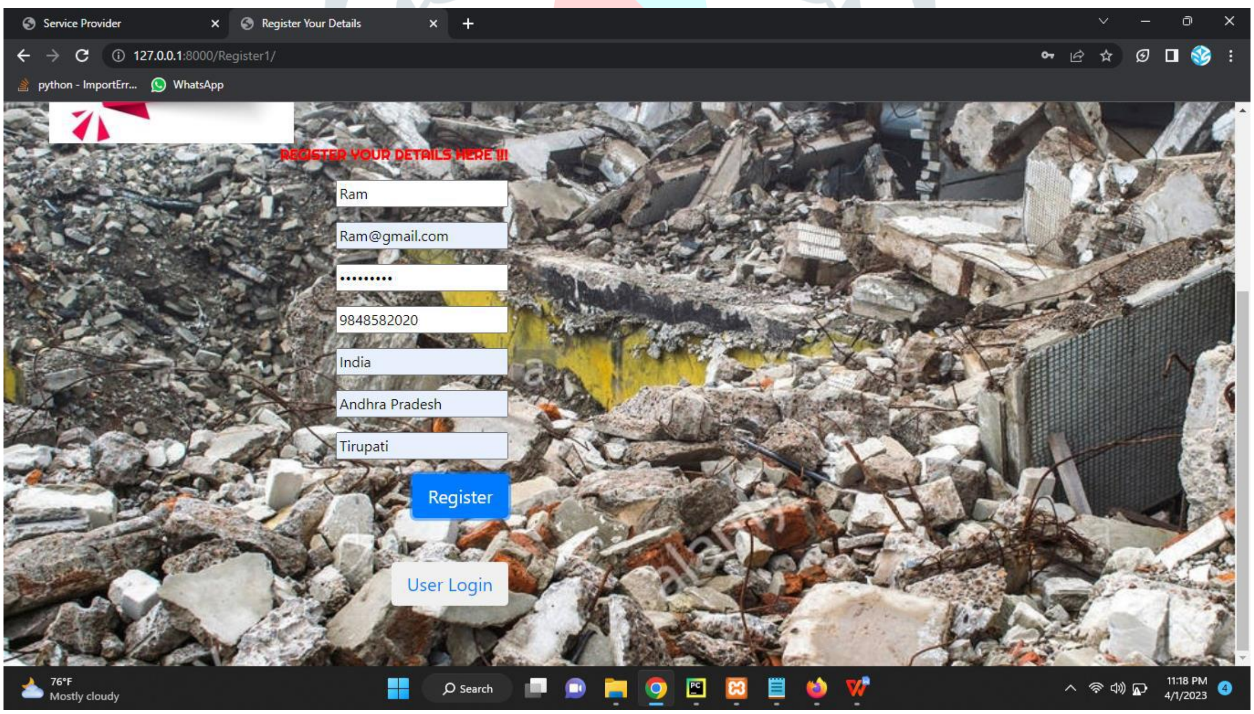
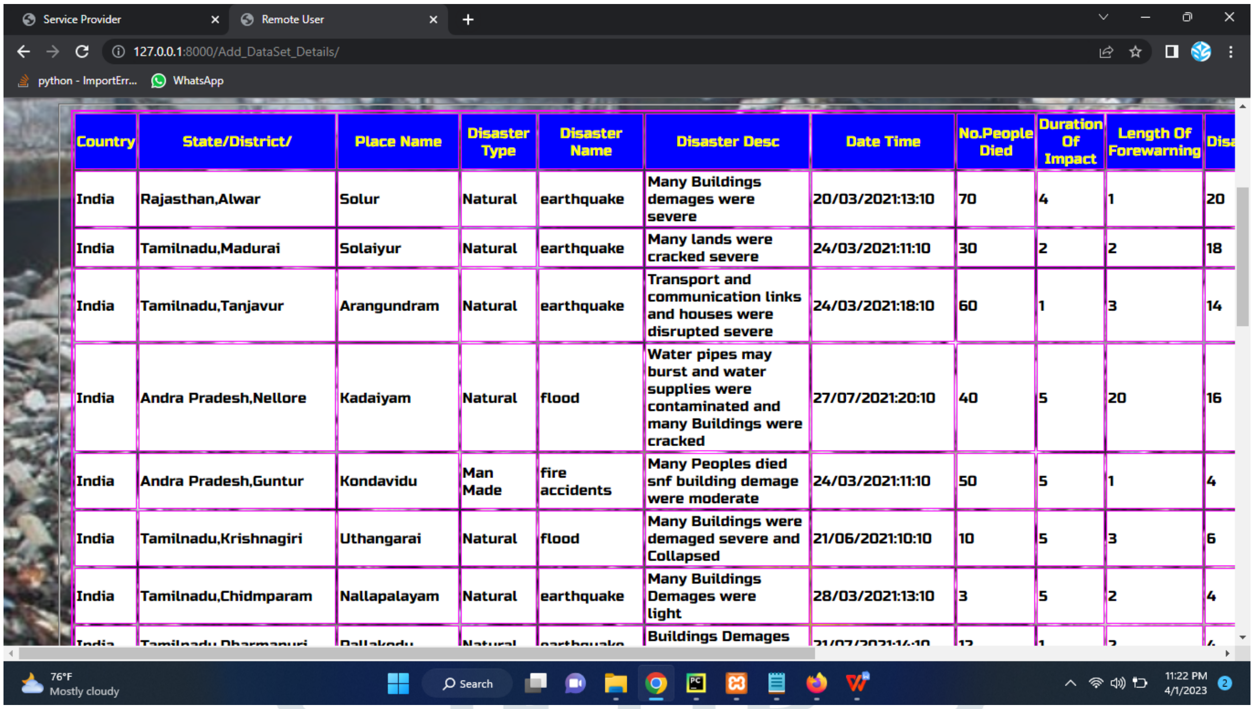


Fig.3 user registration



Country	State/District/	Place Name	Disaster Type	Disaster Name	Disaster Desc	Date Time	No.People Died	Duration Of Impact	Length Of Forewarning	Disa
India	Rajasthan,Alwar	Solur	Natural	earthquake	Many Buildings demages were severe	20/03/2021:13:10	70	4	1	20
India	Tamilnadu,Madurai	Solaiyur	Natural	earthquake	Many lands were cracked severe	24/03/2021:11:10	30	2	2	18
India	Tamilnadu,Tanjavur	Arangundram	Natural	earthquake	Transport and communication links and houses were disrupted severe	24/03/2021:18:10	60	1	3	14
India	Andra Pradesh,Nellore	Kadaiyam	Natural	flood	Water pipes may burst and water supplies were contaminated and many Buildings were cracked	27/07/2021:20:10	40	5	20	16
India	Andra Pradesh,Guntur	Kondavidu	Man Made	fire accidents	Many Peoples died snf building demage were moderate	24/03/2021:11:10	50	5	1	4
India	Tamilnadu,Krishnagiri	Uthangarai	Natural	flood	Many Buildings were demaged severe and Collapsed	21/06/2021:10:10	10	5	3	6
India	Tamilnadu,Chidmparam	Nallapalayam	Natural	earthquake	Many Buildings Demages were light	28/03/2021:13:10	3	5	2	4
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	Buildings Demages	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]

Fig.4 dataset details

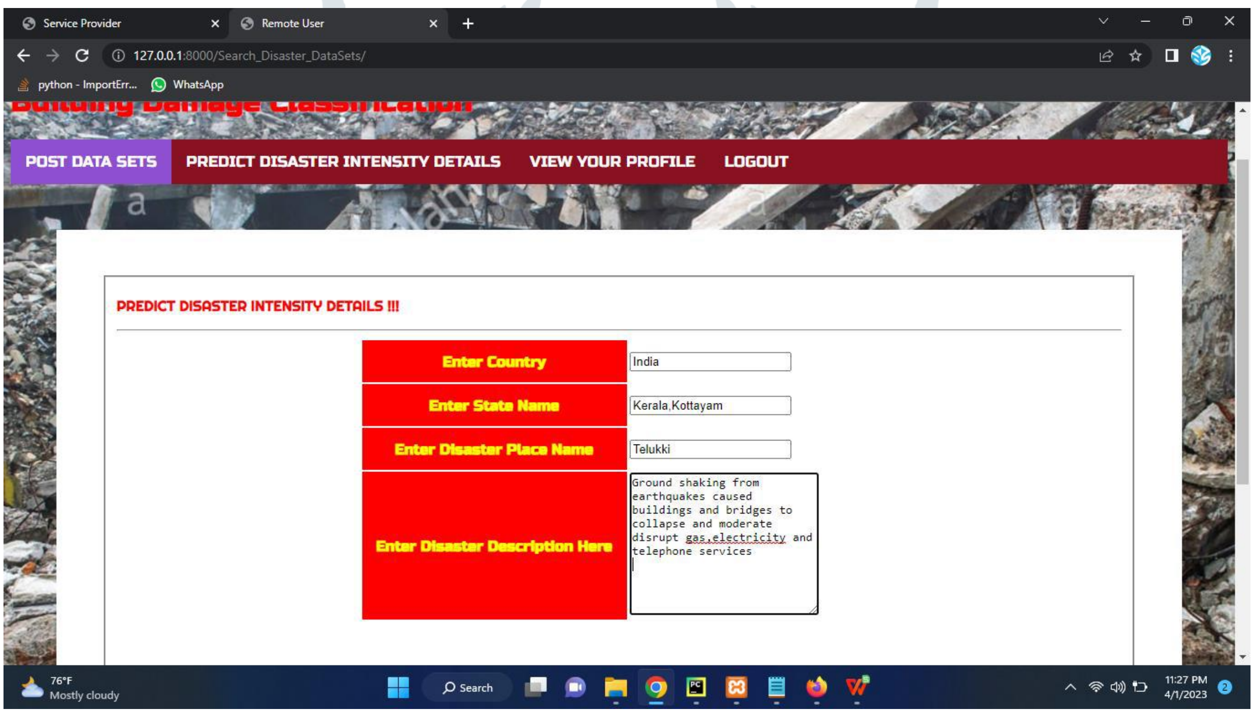


Fig.5 Enter details for prediction

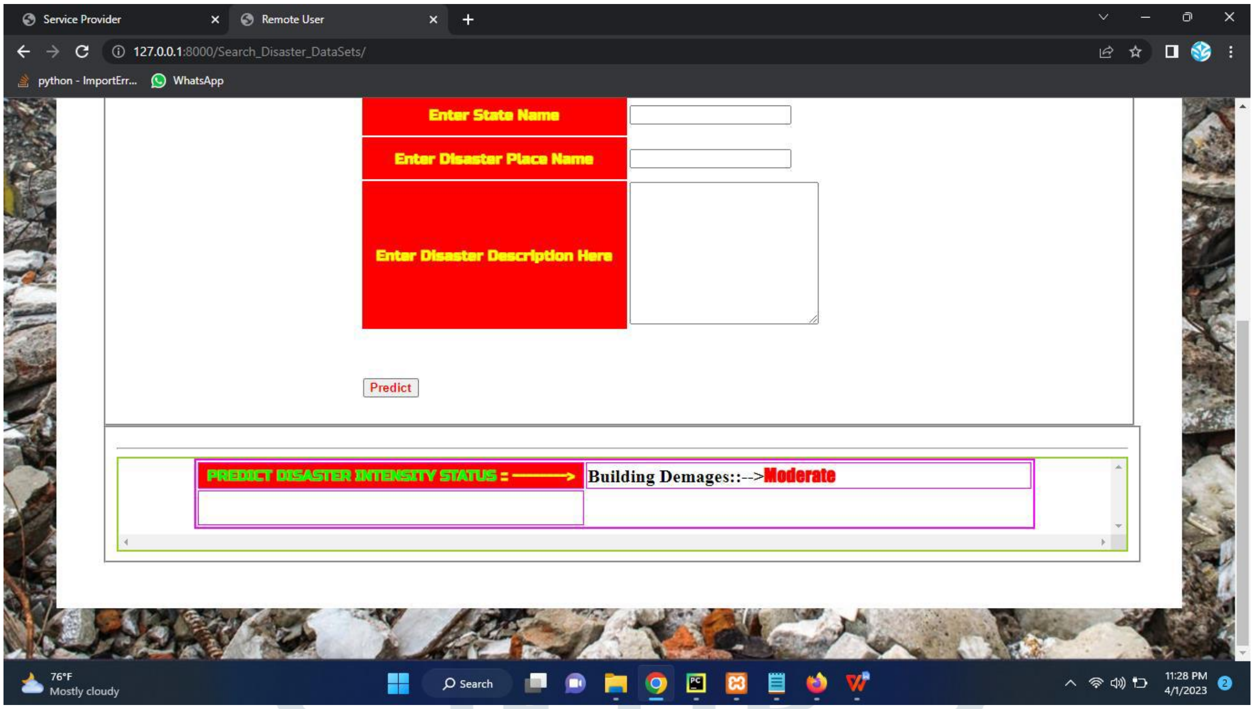
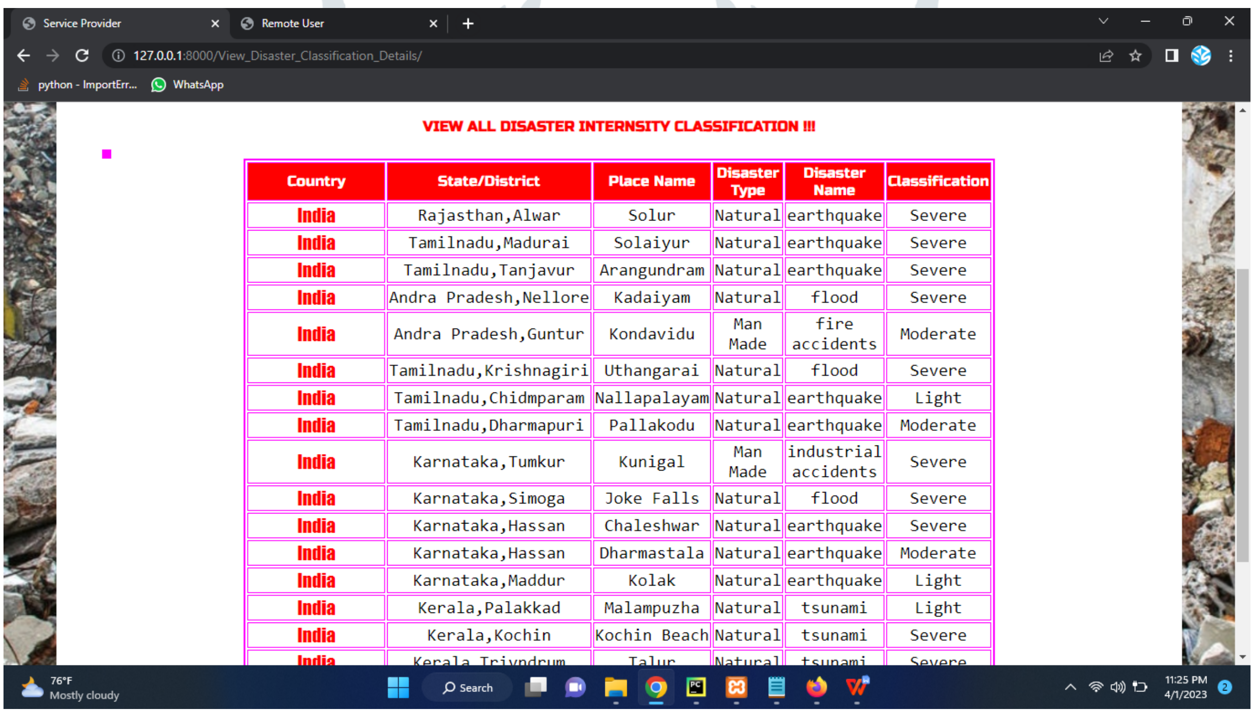


Fig.6 prediction result



Country	State/District	Place Name	Disaster Type	Disaster Name	Classification
India	Rajasthan,Alwar	Solur	Natural	earthquake	Severe
India	Tamilnadu,Madurai	Solaiyur	Natural	earthquake	Severe
India	Tamilnadu,Tanjavur	Arangundram	Natural	earthquake	Severe
India	Andra Pradesh,Nellore	Kadaiyam	Natural	flood	Severe
India	Andra Pradesh,Guntur	Kondavidu	Man Made	fire accidents	Moderate
India	Tamilnadu,Krishnagiri	Uthangarai	Natural	flood	Severe
India	Tamilnadu,Chidmparam	Nallapalayam	Natural	earthquake	Light
India	Tamilnadu,Dharmapuri	Pallakodu	Natural	earthquake	Moderate
India	Karnataka,Tumkur	Kunigal	Man Made	industrial accidents	Severe
India	Karnataka,Simoga	Joke Falls	Natural	flood	Severe
India	Karnataka,Hassan	Chaleshwar	Natural	earthquake	Severe
India	Karnataka,Hassan	Dharmastala	Natural	earthquake	Moderate
India	Karnataka,Maddur	Kolak	Natural	earthquake	Light
India	Kerala,Palakkad	Malampuzha	Natural	tsunami	Light
India	Kerala,Kochin	Kochin Beach	Natural	tsunami	Severe
India	Kerala,Trivndrum	Talur	Natural	tsunami	Severe

Fig.7 View all disaster intensity classification

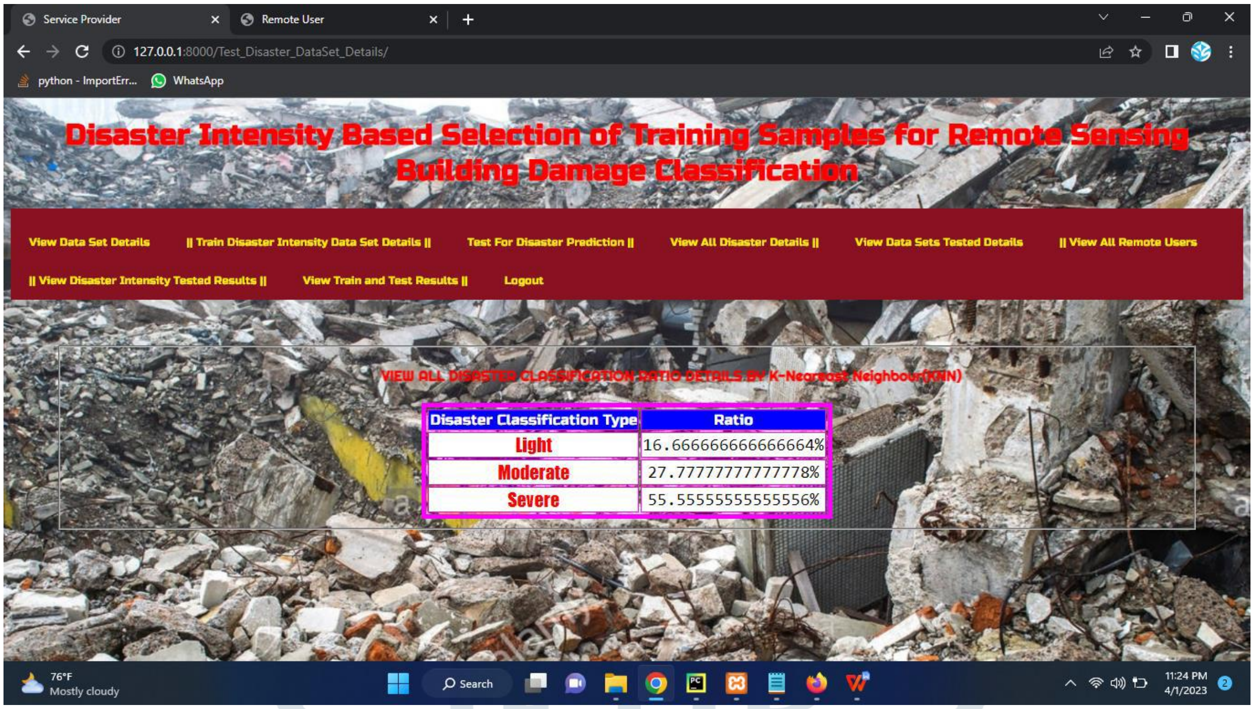


Fig.8 Test For Disaster Prediction

V. FUTURE SCOPE AND CONCLUSION

This Project introduces the use of the demand parameter, which quantifies the disaster intensity, to systematically extract samples from remote sensing imagery and use them to calibrate a change detection classifier. The demand parameter of each sample is estimated via instrumentation and/or numerical simulation, which can be computed in real or near real time.

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