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**Team Title**: Natural Disaster Intensity Analysis And Classification **Members List:** VASU.J

Using Artificial Intelligence RAJAPANDI.K

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| INTRODUCTIO N | | SURVEY/BODY OF REVIEW | | | | | Conclusion | | |
| Year | Title | Keywords | Problem Definition | Methodology (Algorithm,  Protocol…Et c) | Input Parameters | Result | Advantag es | Disadvantage s/Drawbacks | Research  Gap/Research Question |
|  | Natural | deep learning, natural disasters intensity and classificatio n, convolution al neural network | Disaster can be caused by naturally occurring events such as earthquakes  , cyclones, floods, and wildfires. |  |  | The proposed multilaye red deep convoluti onal neural network was simulate d on the computer | the detection of natural disasters by using deep learning techniques still faces various issues due to noise and serious | Disasters may be explosions, earthquakes, floods, hurricanes, tornados, or fires. In a disaster, you face the danger of death or physical injury | The proposed model works in two blocks: Block-I convolutional neural network (B-I CNN), for detection and occurrence of disasters, |
|  | Disasters |  |  |
| 2021 | Intensity Analysis and  Classificati | Neural Network | Image Input Layer Convolutional Layer |
|  | on Based |  |  |
|  | on |  |  |
|  | Multispectr |  |  |

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|  | al Images  Using Multi- |  |  |  |  | system with Core i7, Central Processi ng Unit (CPU)  2.8 Ghz with 16  GB  RAM in MATLA B 2018a  and different types of results were calculate  d. | class imbalance problems |  |  |
| Layered |  |
| Deep |  |
| Convolutio |  |
| nal Neural |  |
| Network |  |
| 2020 | Artificial Intelligenc e for Natural Hazards Risk Analysis: Potential, Challenges  , and Research Needs | artificial intelligence natural hazards predictive modeling | Natural hazards pose significant risks throughout the world.  They are among the deadliest disasters. | Deep Learning | These types of models take as input a spatial field of hazard loading (e.g., maps of predicted wind speeds, soil moisture levels, and other loading measures for a  hurricane or a | We also need to develop better ways of communi cating the results of models, including their  limitatio | But for a model to have sustained accuracy, the conditions above are necessary. | This article takes a critical look at the use of AI for disaster risk analysis. | the forecasting of extreme events and the development of hazard maps to the detection of events in real time, the provision of situational awareness and decision support,  ... |

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|  |  |  |  |  | map of a | ns and |  |  |  |
| ground | uncertain |
| motion | ties, so |
| measure for | that |
| an | decision |
| earthquake) | makers |
| together with | better |
| a set of | understa |
| information | nd and |
| about the | appreciat |
| system, the | e both |
| area, and | the |
| preevent | predictio |
| conditions. | ns and |
|  | the |
|  | limitatio |
|  | ns of |
|  | these |
|  | predictis |
|  | on. |
|  |  | Crowd | OVER the |  | Using the | his surge | ML |  | The objective of this chapter is to show how it is possible to determine damages caused by seismic events in urban areas using optical and radar data, |
|  | Applicatio | evacuation, | last decade, |  | above- | in the | techniques | This article |
|  | n of the | disaster | more than |  | mentioned | number | have the | provides a |
|  | Damage | manageme | 2.6 billion |  | procedure and | of | advantage | literature |
|  | Detection | nt, | humans |  | the SAR | disasters | of | review of state- |
|  | Method | healthcare, | have | Machine | images, the | and | immediatel | of-the-art |
| 2021 | Using SAR | machine | suffered | Learning,Deep | distribution of | pandemi | y filtering | machine |
|  | Intensity | learning | from | Learning | the | cs has | images, | learning (ML) |
|  | Images to | (ML), | catastrophi |  | discriminant | caused a | which | algorithms for |
|  | Recent | pandemic | c disaster |  | score z was | strain on | would have | disaster and |
|  | Earthquake | manageme | outbreaks, |  | formed for | the | required | pandemic |
|  | s | nt, social | such as |  | each | emergen | months to | management. |
|  |  | distancing. | tsunamis, |  | earthquake. | cy | be sorted |  |

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|  |  |  | floods, earthquakes  , cyclones and landslides, and various pandemics |  |  | services, and this is where ML  algorith ms are required to work efficientl y and make the best use of existing  resources | manually. Temporary settlements can also be detected, indicating areas of survivors in need. |  |  |
| 2020 | Automated Identificati on of Disaster News for Crisis Manageme nt using Machine Learning and Natural Language Processing | Crisis, Disaster, Machine Learning, Natural language processing, News, News Classificati on, Pandemic, Scrapy | We are living in unpreceden ted times and anyone in this world could be impacted by natural disasters in some way or the other. Life is unpredictab le and what  is to come | Logistic regression | Word Embedding algorithm is a process in which the input text is converted to the equivalent number representation  . | The evaluatio n metrics taken into consider ation for obtaining the results are precision  , recall, F1 score and confusio n matrix. | A number of researchers have worked on this type of disaster classificatio n either on twitter datasets or on some particular website of news. | The objective here is to automatically scrape news from English news websites and identify disaster relevant news using natural language. | The objective here is to automatically scrape news from English news websites and identify disaster relevant news using natural language |

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|  |  |  | is unforeseea ble. |  |  |  |  |  |  |
| 2020 | Timing is Everything  –Drought Classificati on for Risk Assessmen t | Drought indices, phenology, risk analysis, time series analysis, weighted linear combinatio n (WLC). | It contributes to global food insecurity, environmen tal and economic problems, and ranks first with regard to the number of people affected due to natural hazards on a global scale | Deep learning | input data for further socio- economic analysis with regard to the reporting for the Sendai Framework for Disaster Risk Reduction (SFDRR). | The anomaly detection analysis identifie d different drought and nondrou ght years.  With regard to these results, EVI  phenolog y develop ment as well as VCI  temporal profiles showed clear drops during drought | Remote sensing based drought indices can identify dry periods using, e.g., precipitatio n or vegetation information | Weighted linear combination was applied based on vulnerable vegetation growing stages in the phenology to classify drought severity per season. | A drought risk assessment is a formal step toward identifying vulnerabilities and taking mitigative and adaptive actions to reduce risk. |

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|  |  |  |  |  |  | seasons as well as a shift of the SOS  accordin gly. |  |  |  |
| 2020 | Analysis of Hand- drawn Maps of Places in Natural Disaster Pictures | Human Computatio n, Hand- Drawn Map, Natural Disaster Picture, Location Information | Understand ing the current situation of natural disaster damages is a critical step for an effective natural disaster responses, and many pictures uploaded after natural disasters are valuable resources  for this purpose. | OpenCv | Coordinates of circumscribed circles and polygons. | human participa nts understo od the location relations hip among buildings  , and hand- drawn positions in the birds-eye view map were similar to each other. | This paper explores the potential of human computatio n to solve this problem.  For this study, we asked people to draw a birds-eye view map of the place | When an area is exposed to more than one hazard, a multiple hazard map (MHM) helps the planning team to analyze all of them for vulnerability and risk. | tourism sector may be negatively affected due to labor power decrease and damage in tourism facilities or worsening destination image with respect to bad management of crisis. |

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| 2020 | Emulator of Announcin g Social and Natural Disaster Informatio n for Developin g and Testing UHD-  based Disaster Broadcasti ng System | Natural Disaster, Social Disaster, Emulator, TCAP, UHD | Recently, due to abnormal climate change and the complexity of society, large-scale natural and social disasters occur frequently around the world | Terrestrial Common Alerting Protocol (T- CAP) | The input disaster information is converted into T-CAP so that it can be linked to the currently operating UHD  broadcasting system. | we present the design and impleme ntation results of an emulator that can generate disaster informati on based on T- CAP. | The input disaster information is converted into T-CAP so that it can be linked to the currently operating UHD  broadcastin g system. It also introduced the disaster information delivery process issued by the emulator and introduces the CAP element values specifically defined in  the T-CAP. | This issue of the Supplemental Research Bulletin focuses on how people in poverty, with low incomes, and of low socioeconomic status (SES) experience disasters. | Emulator of Announcing Social and Natural Disaster Information for Developing and Testing UHD-based Disaster Broadcasting System. Conference Paper |

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| 2021 | Estimation of earthquake disaster risk loss based on AHP  method in western China | [Uncertainty](https://ieeexplore.ieee.org/search/searchresult.jsp?matchBoolean=true&queryText=%22Index%20Terms%22%3AUncertainty&newsearch=true)  [.Earthquak](https://ieeexplore.ieee.org/search/searchresult.jsp?matchBoolean=true&queryText=%22Index%20Terms%22%3AEarthquakes&newsearch=true) [es](https://ieeexplore.ieee.org/search/searchresult.jsp?matchBoolean=true&queryText=%22Index%20Terms%22%3AEarthquakes&newsearch=true) | In today's society, earthquake has brought many hazards to us, including but not limited to building collapse, landslide, soil damage, tsunami, fire and so on. These disasters have taken a heavy toll on our economy | Analytic Hierarchy Process (AHP) | From the perspective of earthquake emergency  in China, these data have been named “earthquake emergency foundation data” | The rapid and accurate estimatio n of earthqua ke disaster losses in the period up to 2 h after an earthqua ke is crucial for earthqua ke emergen cy response and rescue | The risk of earthquake disaster in six western provinces of China is evaluated by analytic hierarchy process (AHP), and the evaluation results are compared | Improving earthquake disaster loss estimation speed and accuracy is one of the key factors in effective earthquake response and rescue | IThe prerequisite for earthquake risk estimation is vulnerability assessment.  Therefore, estimating vulnerability is necessary to reduce future |
|  | The Effect of Decision Analysis on Power System Resilience and  Economic | Costs , Tropical cyclones , Wind speed  ,  Simulation  ,  Robustness | Due to climate changes, many natural disasters have  become | Resilient power system | The Effect of Decision Analysis on Power System Resilience and Economic Value during  a Severe | This article proposes an all- inclusive process for  system | The Effect of Decision Analysis on Power System Resilience and  Economic | Impacts of extreme weather events are relevant for regional (in the sense of subnational)  economies and | he objective of this study is to provide a detailed overview of distribution system resilience, the classification, assessment, metrics  for Weather Event. |

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| 2021 | Value during a Severe Weather Event | , Power grids , Power systems | more serious, such as the intensity of typhoons that are getting higher every year.  The characterist ics of such a disaster is high- intensity but low- probability event  (HILP) |  | Weather Event | operators to make decisions for enhancin g power system resilienc e and economi c value | Value during a Severe Weather Even**t**. | in particular cities in many aspects. |  |
| 2021 | A  Planimetric Location Method for Laser Footprints of the Chinese Gaofen-7 Satellite Using Laser Spot Center  Detection | Surface emitting lasers , Laser modes , Cameras , Satellites , Laser beams , Optical imaging , Optical sensors | Satellite stereo mapping, together with laser altimetry, can be used to obtain three- dimensiona l geospatial information  .  Spaceborne | fuzzy edge extraction algorithm | A laser footprint planimetric location method for the Chinese Gaofen-7 satellite is proposed, designed based on the main payload | The experime ntal results show that the accuracy of planimet ric location relative to stereo  image | the laser altimeter together with the footprint camera can provide planimetric geodetic coordinates for the control points of a  higher | The Gaofen-7 (GF-7) satellite is equipped with two area array sensor footprint cameras to capture the laser altimeter spot. | A Planimetric Location Method for Laser Footprints of the Chinese Gaofen- 7 Satellite Using Laser Spot Center Detection and Image Matching to Stereo Image Product. |

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|  | and Image Matching to Stereo Image Product |  | laser altimeter can provide high- accuracy elevation information |  |  | for the laser footprint is 0.3–  1.0 m (except for ice sheets  ~12 m) when the footprint camera works under the synchron ous mode, and 0.2–  0.4 m when the footprint camera  works under asynchro nous mode | accuracy than the other traditional satellite laser altimeters, and represents a new technology for satellite mapping**.** |  |  |