IJCRT.ORG ISSN : 2320-2882

INTERNATIONAL JOURNAL OF CREATIVE RESEARCH THOUGHTS (IJCRT)

An International Open Access, Peer-reviewed, Refereed Journal

AI/ML BASED FLOOD PREDICTION USING GIS APPLICATION

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Abstract: Floods pose significant risks to human lives and infrastructure worldwide, necessitating accurate prediction and timely response strategies. This study proposes an Artificial Intelligence (AI) and Machine Learning (ML) approach to predict flood intensity and evaluation human headcount inflood-affected areas. Leveraging historical flood data, atmospheric parameters, terrain features, and satellite imagery, our model employs advanced AI algorithms, including deep learning neural networks and ensemble methods. Firstly, flood intensity prediction is addressed using a amalgamation of convolutional neural networks (CNNs) and recurrent neural networks (RNNs) to evaluate spatiotemporal patterns and predict flood levels with high exactness. Secondly, human headcount estimation utilizes a hybrid model incorporating support vector machines (SVMs) and random forest algorithms trained on socio-demographic data, population densities, and real-time information from social media and disaster retort agencies. The proposed AI/ML framework offers several advantages, including real-time monitoring, early caution systems, and efficient resource allocation during flood events. Validation against historical flood incidents establishes the model's robustness and effectiveness in predicting flood intensity and estimating human headcount. Integration of this technology into prevailing disaster management systems can enhance preparation, response, and recovery efforts, ultimately modifying the adverse impacts of floods on communities and organization..

***Index Terms* - Component, formatting, style, styling, insert.**

I. INTRODUCTION

Floods are among the most devastating natural disasters, causing extensive destruction to lives, property, and infrastructure globally. With climate change exacerbating extreme weather events, the need for accurate flood prediction and effective response strategies has become paramount. Traditional flood prediction methods often rely on simplistic models that lack the capacity to account for complex spatiotemporal dynamics and socio- demographic factors, leading to ridiculous preparation and response efforts.

To address these challenges, this study proposes an innovative approach leveraging Artificial Intelligence (AI) and Machine Learning (ML) techniques for predicting flood intensity and estimating human headcount in flood-affected areas. By attaching the power of AI algorithms, including Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), Support Vector Machines (SVMs), and collective methods, our framework aims to improve the accuracy and efficiency of flood forecasting and disaster management.

The prediction of flood intensity is a critical aspect of disaster preparation, as it enables authorities to anticipate the severity of flooding events and allocate resources accordingly. By integrating historical flood data, meteorological parameters, terrain geographies, and satellite imagery, our AI/ML model can analyze complex spatiotemporal patterns and provide real-time forecasts of flood levels with high precision.

Furthermore, estimating human headcount in flood-affected areas is vital for organizing rescue and relief operations and ensuring the safety and well-being of affected populations. Our hybrid model combines socio-demographic data, population densities, and real-time information from social media and disaster response agencies to accurately estimation the number of people impacted by floods.

Overall, the integration of AI/ML techniques into flood prediction and human headcount guesstimate holds great promise for enhancing disaster resilience and mitigating the adverse impacts of floods on communities and infrastructure.

II. LITERATURE SURVEY:

In[1], The classification of hyperspectral image (HSI) has attracted significant attention from the research community of remote sensing. HSI analysis suffers from overfitting due to the limited number of labelled training samples. As a result, to enhance the performance of the HSI classification task, a better efficient neural network architecture should be developed. To tackle this issue, this letter presents a new 3D-Inception CNN (3D-ICNN) model for dynamically extracting features by stacking inception modules in the network that can learn more representative features with fewer training samples by adopting variable spatial size convolutional filters and dynamic CNN architecture.

In[2], Deep convolutional neural networks (CNNs) have shown their outstanding performance in the hyperspectral image (HSI) classification. The success of CNN-based HIS classification relies on the availability of sufficient training samples. However, the collection of training samples is expensive and time-consuming. Besides, there are many pre-trained models on large-scale data sets, which extract the general and discriminative features. The proper usage of low-level and midlevel representations will significantly improve the HIS classification accuracy. The large-scale Image Net data set has three channels, but HIS contains hundreds of channels. Therefore, there are several difficulties in simply adapting the pre-trained models for the classification of HSIs. In this article, heterogeneous transfer learning for HSI classification is proposed.

In[3], Deep neural networks (DNNs) have emerged as a relevant tool for the classification of remotely sensed hyperspectral images (HSIs), with convolutional neural networks (CNNs) being the current state-of-the-art in many classification tasks. However, deep CNNs present several limitations in the context of HSI-supervised classification. Although deep models can extract better and more abstract features, the number of parameters that must be fine-tuned requires a large amount of training data (using small learning rates) to avoid overfitting and vanishing gradient problems. The acquisition of labelled data is expensive and time consuming, and small learning rates force the gradient descent to use many small steps to converge, slowing down the runtime of the model.

III. PROPOSED METHODOLOGY

The methodology for the proposed AI/ML-based flood intensity prediction and human headcount estimate framework

Involves several key steps. Firstly, data preprocessing is conducted to gather and clean relevant datasets, as well as historical flood data, meteorological parameters, socio-demographic information, population densities, and satellite imagery. This step ensures the quality and compatibility of the input data for subsequent analysis. Next, the flood intensity prediction module utilizes machine learning procedures such as Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) to examine spatial and temporal patterns associated with flood occurrences. Satellite imagery, territory features, and historical flood data are input into the model to predict the possibilities and severity of flooding in different regions. Simultaneously, the human headcount estimation module employs algorithms like Support Vector Machines (SVMs) to analyze socio-demographic data and population densities, estimating the number of people affected by floods. This module takes part real-time data from social media and disaster response agencies to increase accuracy. Finally, an ensemble integration module combines predictions from multiple models, enhancing overall performance and robustness. Collective methods such as Random Forests or Gradient Boosting are active to integrate predictions from the flood intensity prediction and human headcount estimation modules. By gathering predictions, the basis provides accurate flood predictions and human headcount estimations, simplifying more effective disaster management strategies.

FLOOD PREDICTION INTENSITY:

Floods are among the most overwhelming natural disasters, necessitating accurate estimate methods to mitigate their

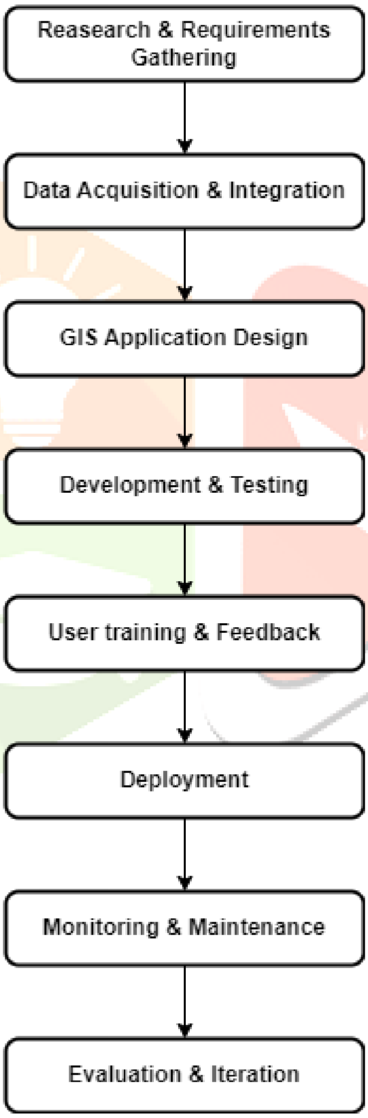
impact. This study presents a pioneering approach leveraging Artificial Intelligence(AI) and Machine Learning (ML) techniques

for predicting flood intensity with improved accuracy and efficiency. By take part historical flood data, meteorological parameters, terrain features, and satellite imagery, our AI/ML model employs advanced algorithms such as Convolutional

Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) to analyze complex spatiotemporal patterns associated with flood occurrences. CNNs are exploited to extract features from satellite imagery and terrain data, while RNNs capture temporal dependances in historical flood data. This enables the model to predict flood intensity levels in different regions with high precision. Validation against historical flood incidents validates the robustness and effectiveness of the proposed approach in accurately forecasting flood intensity. The addition of AI/ML techniques into flood intensity prediction offers several advantages,

including real-time monitoring, early warning systems, and improved disaster preparedness. By providing timely and accurate predictions, our model enhances the ability of authorities to allocate resources efficiently and implement effective mitigation measures, at last reducing the impact of floods on groups and infrastructure.

IV. BLOCK DIAGRAM:



V. PROPOSED ALGORITHM:

CONVOLUTIONAL NEURAL NETWORKS (CNNS):

CNNs are a class of deep learning neural networks commonly applied to analyze visual imagery. In the context of flood intensity prediction, CNNs are utilized to process satellite imagery and terrain features, extracting relevant spatial information to predict the severity of flooding in different areas. By leveraging the hierarchical structure of CNNs and their ability to automatically learn structures from raw data, they enable the model to capture complex spatial patterns connected with flood intensity.

RECURRENT NEURAL NETWORKS (RNNS):

RNNs are a type of neural network well-suited for processing sequential data with temporal dependencies. In the framework, RNNs are employed to analyze historical flood data, capturing temporal patterns and trends in flood manifestations over time. By processing sequential flood data, RNNs enable the model to understand how flood intensity evolves over time, enlightening the accuracy of flood intensity predictions.

SUPPORT VECTOR MACHINES (SVMS):

SVMs are a class of supervised learning algorithms used for classification and regression tasks. In the context of human
headcount estimation, SVMs are used to analyze socio-demographic data and population densities. By identifying patterns and relationships in socio-demographic features, SVMs enable the model to approximation the number of people affected
by floods in different regions accurately.

ENSEMBLE METHODS:

Ensemble methods combine predictions from multiple machine learning models to improve overall presentation. In the
Framework, ensemble methods such as Random Forests or Gradient Boosting are applied to take part predictions from CNNs, RNNs, and SVMs. By leveraging the diversity of individual models and combining their predictions, ensemble methods enhance the robustness and accuracy of both flood intensity prediction and human headcount estimation.

VI. SATELLITE IMAGES:

Training machine learning models with satellite images includes several key steps. First, collect a diverse dataset of satellite images capturing various flood scenarios, along with corresponding labels indicating the intensity of flooding. Preprocess the images by resizing, standardizing, and augmenting to enhance data quality and diversity. Extract meaningful features from the images using techniques like deep feature abstraction from pre-trained convolutional neural networks (CNNs). Next, split the dataset into training and validation sets. Choose an appropriate machine learning model architecture, such as CNNs, for image classification tasks. InterCity the model using the training data, adjusting model parameters and hyper parameters as needed. Evaluate the trained model's performance on the justification set using metrics like accuracy and F1-score. Finally, deploy the accomplished model for expecting flood intensity on new satellite images, ensuring scalability and efficiency for real-world applications. Regularly keep informed and retrain the model to maintain its exactness and proficiency over time.

METHOD:

The methodology for AI/ML-based estimation of human headcount in flood-affected areas involves an organized method encompassing several key modules. Firstly, the Data Collection Module is responsible for assembly diverse datasets including socio-demographic information, population density maps, and real-time data from sources such as census records, satellite imagery, social media, and disaster response agencies. Subsequently, the Data Preprocessing Module cleans and preprocesses the collected data to ensure consistency, handle missing values, and normalize features for further analysis. The Feature Engineering Module excerpts relevant features from the data, such as demographic attributes and residents' density patterns, to serve as input for the machine learning model. Next, the Machine Learning Model Selection Module chooses appropriate algorithms considering the characteristics of the data and the complexity of the task. Commonly employed algorithms include Support Vector Machines (SVMs), Random Forests, or Gradient Boosting Machines. The selected model is then trained using the Training Module, where socio-demographic characteristics and population density information are used as input features, and human headcount serves as the target variable. Following training, the model's performance is gauged and validated using the Validation Module, ensuring its accuracy and generalization to unseen data. Hyper parameter tuning is performed to optimize the model's performance through the Hyper Parameter Tuning Module. Upon successful validation, the model is integrated into a larger disaster supervision system via the Integration Module, where it receives real-time data inputs and provides estimates of human headcount in flood-affected areas. Finally, the Positioning Module deploys the integrated system for effective use, ensuring scalability, reliability, and efficiency in estimating human headcount during flood events.

Continuous monitoring and maintenance are carried out through the Monitoring and Preservation Module to ensure the system's success over time. This comprehensive methodology enables accurate and timely guesstimate of human headcount, enhancing disaster response efforts in flood-affected regions.

- ✓ DATA COLLECTION:

Gather satellite images covering areas prone to flooding during historical flood events. These images should capture various flood scenarios, including different levels of intensity and extents.

- ✓ IMAGE PREPROCESSING:

Preprocess the satellite images to enhance their suitability for training. This may involve tasks such as image resizing, normalization, and filtering to improve image quality and consistency.

- ✓ ANNOTATION:

Annotate the satellite images to label regions affected by flooding and specify the intensity levels. This annotation process provides ground truth data for training the model and involves marking flooded areas with equivalent intensity levels.

- ✓ FEATURE EXTRACTION:

Extract relevant features from the annotated satellite images. These features may include water bodies, changes in territory elevation, land cover types, and other spatial characteristics connected with flood events.

- ✓ MODEL SELECTION:

Choose an appropriate machine learning model for flood concentration prediction using satellite images. Convolutional Neural Networks (CNNs) are commonly used for image classification tasks and are well-suited for examining spatial patterns in satellite imagery.

- ✓ TRAINING:

Train the selected model using the annotated satellite images and consistent intensity labels. During training, the model learns to classify forms and relationships between image features and flood intensity levels.

- ✓ VALIDATION:

Validate the trained model using a separate dataset of satellite images not used during training. This step guarantees that the model generalizes well to unseen data and correctly predicts flood concentration levels.

- ✓ FINE-TUNING:

Fine-tune the model as necessary to improve its performance. This may involve adjusting hyperparameters, refining feature extraction techniques, or incorporating additional data sources to develop prediction accuracy.

- ✓ DEPLOYMENT:

Deploy the trained model for real-time flood passion prediction applications. Integrate the model into a system capable of processing incoming satellite imagery and providing timely flood intensity forecasts to aid disaster response efforts.

- ✓ EVALUATION:

Evaluate the trained model's performance using metrics such as accuracy, precision, recall, and F1-score. Assess the model's ability to exactly predict flood intensity levels based on unseen satellite images

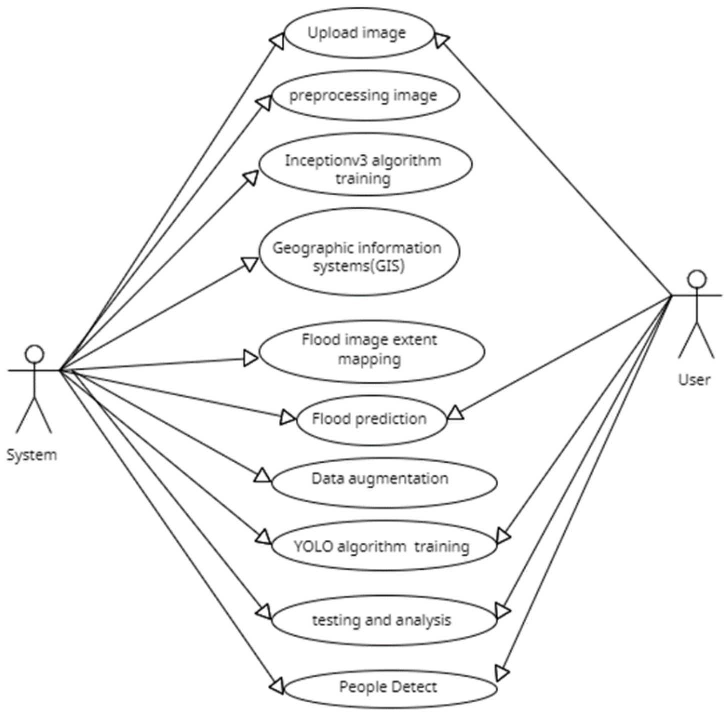
VII. ESTIMATION OF HUMAN HEADCOUNT IN FLOOD:

Accurate estimation of human headcount in flood-affected regions is crucial for effective disaster response planning and resource allocation. This study proposes an innovative approach leveraging Artificial Intelligence (AI) and Machine Learning (ML) techniques for assessing human headcount in flood-prone areas. By integrating socio-demographic data, population density maps, and real-time evidence from social media and disaster response agencies, our AI/ML model employs procedures such as Support Vector Machines (SVMs), Random Forests, or Gradient Boosting Machines. Through data preprocessing and feature engineering, related socio-demographic attributes and population density characteristics are extracted to serve as input features for the model. The model is trained on historical data and validated to ensure its accuracy and consistency in estimating human headcount during flood events. The integration of AI/ML techniques into human headcount estimation increases the appropriateness and precision of disaster response efforts, enabling authorities to allocate resources efficiently and prioritize areas most in need of assistance. The proposed framework offers a scalable and adjustable solution for approximating human headcount in real-time, thus facilitating more effective and targeted disaster management strategies. By connecting the power of AI and ML, we aim to improve the resilience of communities and minimalize the adverse impact of floods on human lives and infrastructure.

WORKING PROCESS FOR INCEPTIONV3:

In the InceptionV3 algorithm plays a pivotal role in predicting flood levels based on satellite imagery. The working process of InceptionV3 involves several key steps. Initially, satellite images depicting flood-prone areas are collected and preprocessed to enhance quality and consistency. Preprocessing steps may include correcting sensor distortions, removing noise, and aligning images to a common spatial reference system. Once preprocessed, the satellite images are fed into the InceptionV3 algorithm for feature extraction and flood level prediction. InceptionV3, a convolutional neural network (CNN), is adept at recognizing patterns and features within images. The algorithm extracts relevant features from the satellite imagery, such as water extent, land cover, and terrain elevation, which are indicative of flood levels. These features serve as input to the neural network, which has been trained on a dataset of historical flood data to learn the relationships between input features and flood levels. During the prediction phase, the InceptionV3 algorithm analyses the extracted features and generates predictions for the severity and extent of flooding in the target areas. These predictions provide valuable insights for proactive flood management strategies, enabling decision-makers to assess risk, allocate resources, and implement timely response measures. Through its integration into the proposed flood management system, InceptionV3 enhances prediction accuracy and facilitates informed decision-making, ultimately contributing to more effective disaster preparedness and response efforts.

FLOW CHART:



ADVANTAGES OF SYSTEM TESTING:

- It includes all software through end- to-end software testing. As a result, you can be sure that the integration ofyour business necessities and your software architecture is working well.
- Detects errors that occur when your application is released to customers. Build your team's confidence in your product before acceptance testing.
- Since this is a form of black box testing, testers do not need to know programming to complete these tests.
- Various test scripts are used to authorize the entire system's functionality and meet the customer's Technical and business needs.

VIII. WORKING PROCESS FOR INCEPTIONV3:

In the InceptionV3 algorithm plays a pivotal role in predicting flood levels based on satellite imagery. The working process of InceptionV3 involves several key steps. Initially, satellite images depicting flood- prone areas are collected and preprocessed to Enhance quality and consistency. Preprocessing steps may include correcting sensor distortions, removing noise, and aligning images to a common spatial reference system. Once preprocessed, the satellite images are fed into the InceptionV3 algorithm for feature extraction and flood level prediction. InceptionV3, a convolutional neural network (CNN), is adept at recognizing patterns and features within images. The algorithm extracts relevant features from the satellite imagery, such as water extent, land cover, and terrain elevation, which are indicative of flood levels.These features serve as input to the neural network, which has been trained on a dataset of historical flood data to learn the relationships between input features and flood levels. During the prediction phase, the InceptionV3 algorithm analyses the extracted features and generates predictions for the severity and extent of flooding in the target areas. These predictions provide valuable insights for proactive flood management strategies, enabling decision-makers to assess risk, allocate resources, and implement timely response measures. Through its integration into the proposed flood management system, InceptionV3 enhances prediction accuracy and facilitates informed decision-making, ultimately contributing to more effective disaster preparedness and response efforts

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IX. CONCLUSION

In conclusion, the integration of Geographic Information System (GIS) applications with advanced deep learning algorithms, such as InceptionV3 and YOLOv8, represents a significant advancement in flood management practices. Through the fusion of spatial data analysis capabilities and state-of-the-art image processing techniques, the proposed system offers a comprehensive framework for proactive disaster alertness and response. By harnessing the power of GIS technology, stakeholders can visualize flood-prone areas, assess vulnerability, and develop targeted strategies for mitigation and response. Additionally, the incorporation of advanced deep learning algorithms improves flood prediction accuracy and enables real-time detection of individuals in flood-affected areas, aiding timely and effective emergency response efforts. Overall, the proposed system holds immense potential to mitigate the impact of floods, safeguard communities, and save lives in the face of intensifying flood risks exacerbated by climate change.

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