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A Multi-Hazard Weather and Disaster Prediction Mobile Application

Arijit Sarkar, Arnab Maity, Basundhara Sarkar, Aritree Roy, Aranaya Roy, Ashu Shaw, Anurima Majumdar, Koushik Pal, Antara Ghoshal
Department of Electronics and Communication Engineering (2nd year)
Guru Nanak Institute of Technology (of JIS group), Kolkata, West Bengal
sarkararijit@gmail.com, arnabmaity538@gmail.com, basundharasarkar076@gmail.com
aritreeroy20@gmail.com, aranayaroy7@gmail.com, shawashu06@gmail.com
anurima.majumdar@gnit.ac.in, koushik.pal@gnit.ac.in, antara.ghoshal@gnit.ac.in

Abstract: *The present work details the development of a mobile application that includes real-time weather forecasts, climate trend information, and multi-hazard disaster forecasting for earthquakes, tsunamis, and flooding– all presented via an interactive map interface. The application allows users to sign in, use custom settings, and search any place on Earth to view the current weather and multi-day hazards. The user app provides early warning features to enhance community resiliency. This application positively contributed through the consolidation of meteorological and geophysical data, interactive mapping services, and secured access for users. A prototype was tested to conduct an evaluation for user testing and testing for accuracy across the back-end models. The results of data collected indicate that users were extremely satisfied with the experience, and the accuracy of data predictions via climate trends for disaster and multiple types of hazard phenomena exceeds and is comparable to stand-alone environmental hazard predictions. We will argue that this application can positively advance readiness and response in disaster behaviors.*

Keywords: *mobile application*

I. INTRODUCTION

Natural hazards, such as weather-related events and geophysical disasters, are an increasing risk to lives and the built environment. Although weather apps provide forecasts, and specific systems issue hazard warnings (e.g., ShakeAlert for earthquakes), there is no single, global, multi-hazard risk assessment mobile application. This study aims to fill that gap, by developing a mobile application that:

- Forecasts weather on short-term time-scales, and analyses climate trends,
- Evaluates multi-hazard risk at user-defined locations,
- Communicates data via real-time interactive maps,
- Supports user authentication and privacy.

This integrated application supports the Multi-Hazard Early Warning Systems (MHEWS) concept from the Sendai Framework.

II. LITERATURE SURVEY

Advances in research on disaster forecasting and weather applications have increased in scale and scope, particularly in the areas of machine learning and remote sensing.

Regarding the area of anticipated floods, Mosavi et al. [15] conducted an overview of machine learning techniques, and Syeed et al. [5] focused on comparing algorithms, accuracy, and efficiency of forecast legends. Hofmann and Schüttrumpf [8] evaluated a real-time flood forecasting model using generative adversarial networks (GANs).

In terms of earthquakes and structural collapse. Visuri et al. [2] showed smartphone-based sensing using accelerometers, and Yi et al. [16] built an artificial intelligence (AI) and neuro-fuzzy system. Arslan et al. [13] reviewed landslide detection from satellite and deep learning.

Choi et al. [3] examined crowdsourced data from disasters through clustering for images to determine damage, and Sun et al. [12] reviewed AI-based communication platforms that impacted hazard/risk reduction. Linardos et al. [14] implemented AI for logistics for emergency infrastructure forecasts during emergency management.

About tsunami forecasting, Galaz et al. [7] developed a GPU-accelerated simulated framework for tsunami simulations, while Srivihok et al. [18] provided a risk estimate system. Yang et al. [19] suggested a global technology-based early warning system composed of different sources of heterogeneous data and systems.

Bui et al. [11] presented an artificial neural network (ANN) for storm surge storms in the coastal areas of Vietnam. Izadi and Hajibabaei [9] suggested a memory-augmented network (MAN) for weather-based models to improve forecasts. Chang et al. [20] combined a NexGen regression-linear model with an artificial neural network (ANN) in a hybrid method for short-term flooding forecasting purposes.

Ogie et al. [10], Tamburri et al. [6], and Goswami and Chakrabarti [17] looked at how large-scale data management takes on a role in early warning systems, specifically big data and data mining as aspects of predictive analytics.

Overall, this literature provides a strong basis to develop our multi-hazard mobile app.

III. NOVELTY OF THE RESEARCH

The weather app offers an unparalleled opportunity to utilize climate data and predictive modeling for multiple natural disasters; all in one application. Unlike most weather apps available today, which chiefly monitor only current conditions or future weather, this weather app documents location-based predictive analytics for multiple hazards such as earthquakes, tsunamis, floods, and other hazards, complementing user awareness and preparedness. The application has a global interactive map component and will allow users the ability to document the risks of disaster globally, not just via localized services. While user authentication allows the app to personalize configurations, the app continues to preserve user privacy. By offering a real-time common weather update application integrated with climate trend and multi-hazard risk predictive analytics, the weather app represents a new framework of disaster adaptation and early warning.

IV. METHODOLOGY

The Natural Disaster Alert and Weather Prediction system will adopt a component-oriented, modular approach for development. The system will provide secured access control, process dynamic data, and determine risk by location. The Natural Disaster Alert and Weather Prediction system will be one application to provide alerts, and weather data allowing users to take safe action. The following are the main modules that will be developed with this approach:

A. User Authentication:

The User Access & User Environment Module governs user access controls and user environment (audit trail). The users will require secure access to the application and person-based.

- **Login:** Authenticate returning users through credentials that allow access to user accounts.
- **Registration:** Allow new users authorization to create accounts through general information required.
- **Profile Management:** Allow users to update identification information and customize alerts and saved places.

B. Data Management:

This section describes two additional forms of data, internal and external, and primarily ensures that the system is working correctly and up to date.

i. Local Storage:

- **User Data**: is used to store credentials, preferences, and notification settings.
- **Geolocalization Data**: is used to store the data about the places a user went to often or searched recently just to help them easily find the locations again if or when they want to.

ii. API Integration:

- **Weather Services**: provides copyright weather updates based on the determined search location and predicts weather in the immediate future based on what the user searched.
- **Geocoding Services**: takes the name of the location and returns an associated latitude and longitude.
- **Risk Analysis Engine**: Takes the various parameters and formatting based on the Environmental data to track common levels of risk or threat.

C. Core Functional Features:

This user interface is where users interact with the system. It provides information on; Disaster incidents, Weather patterns, and Safety recommendations

i. Risk Map:

- **Interactive Display:** Allows users to display the areas of varying risk.
- **Map Search:** Provides users the ability to search for locations to assess current risk levels.
- **Risk Icons:** Displays hazard indicators using color-coded or symbol-based markers.

ii. Weather Reporting:

- **Current Reporting:** Provides users with current precipitation conditions (in real-time).
- **Short-Term Reporting:** Provides users with a two-day forecast for users to plan for.
- **Warnings:** Provides users with alerts for hazardous or unusual weather conditions.

iii. Risk Assessment:

- **Input Variables:** Reviews and assesses an input dataset of factors such as; precipitation counts, topography, and temperature.
- **Calculated Risk Level:** Predicts a risk level based upon probability and thresholds dictated by an algorithm.
- **Recommended Actions:** Delivering user safety actions that are determined based on the current assessment risk and risk associated with the previous incidents.

iv. Place information:

- **Place Characteristics**: Provides user with environmental and place characteristics and metadata
- **Incident History**: Provides the ability to access historical incidents for the selected location.

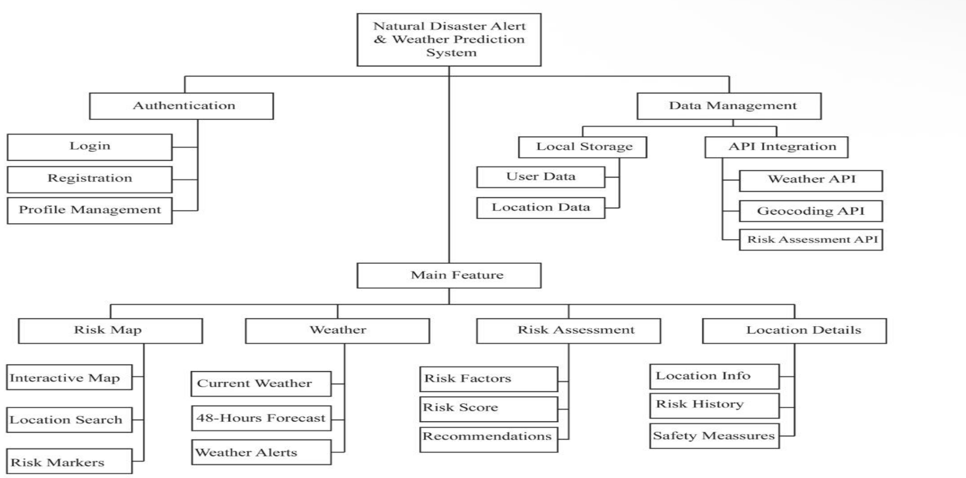
- **Preparedness Advice**: Provides action steps before, during, and after emergency events

D. Solution Implementation:

The solution was developed and implemented using scalable, cloud-based, agnostic technologies to maximize our future continuous improvement and developability.

- **Front end:** The solution was developed using React Native to support both Android and ios applications.
- **Back end:** The solution was developed using Node.js or Flask to allow for a lightweight and efficient platform to handle such requests and facilitate processing the information.
- **Database:** The solution uses Firebase to allow users secure credential information, settings and location information stored in the cloud.
- **Push Notifications:** The solution is using the services of OneSignal, or Firebase Cloud Messaging to enable real-time alerts and warnings.

E. Flowchart:



F. Approach on Developing the Mobile Solution:

The mHealth technology -built as a user generated and staged process including different stages- looked like this:

i. Understanding User Needs:

Household demands were garnered through targeted interviews and focus group discussions with consumers, first responders and climate scientists. The following were the main findings:

- Weather Surveillance and Reatime Environmental User hreat Prediction
- An interactive, geolocated map.
- Multiday risk projections.
- Two different users for two different profiles.

This stage had focused on following question: who was the app for?

ii. Design System Architecture :

In practice, a modular architecture was created for maintainability and scalability. Every facet of the system is as follows:

- **Frontend:** The frontend of the applications for both Android and iOS were developed in React Native.
- **Backend:** The back-end utilizes Firebase Authentication for login features, and Firestore is used for data.
- **API Services:** OpenWeatherMap API, USGS (earthquake precedents), and Mapbox (mapping) were integrated for API services.
- **Predictin Engine:** The Prediction Engine is hosted in the cloud (AWS) via Python Flask APIs.

The utilization of RESTful endpoints will enable every modular part of the system to work together with real-time updates.

iii. UI/UX Design:

The idea behind the app model was to create something friendly and simple to use to create a design and make it with Figma. The main features include:

- A home page that lists the hazard and provides the current weather
- Map of hazard levels across the world, by region
- Tabs to navigate between hazard types.
- Settings and Alerts, customers can setup each of their preferences

The risk is graphically shown with color traffic lights (green, yellow, red).

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iv. Model Merging:

Two types of model predictions that have been used:

- **Meteorological Forecast:** LSTM and Random Forest (RF) models were trained based on historical climate data.
- **Components of Hazard Risk Assessment:** A scenario based on a Bayesian network was developed that incorporated weather destination anomalies, seismic activity events, and hydrological retrospective history.

The model output that is being retrieved is dynamically either geolocation on screen, to indicate various timeframes to use the model outputs to inform the user. The alert logic was utilized to produce messages for exceedance thresholds for escalating hazards.

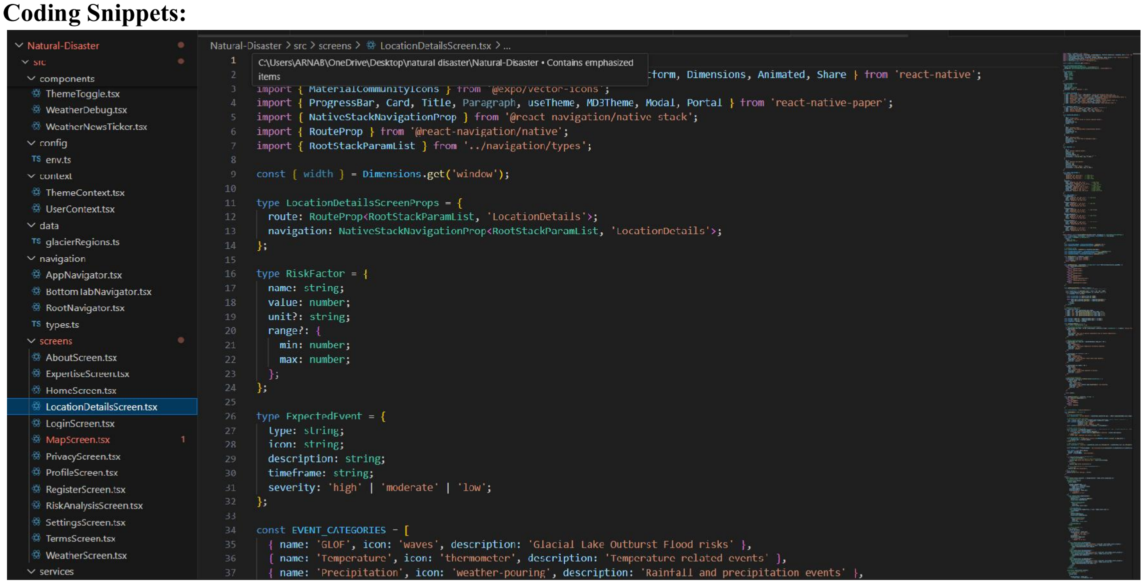
v. Test and Refine:

Testing occurred in two phases:

- **System Testing:** validated the expected action of all functional modules including login; mapping; notifications and retrieving data.
- **User Testing:** occurred with 20 users and involved user tasks with an app and evaluated the usability of the interface, understanding of the risk and responses to alerts.

Based on user feedback improvements were made to: wording of alerts and notifications; improved interface responsiveness; clarity of the map; performance enhancements through optimizing load time and predictability/reliability of the system.

G. Coding Snippets:



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```
Natural-Disaster > src > screens > RiskAnalysisScreen.tsx > ...
import React, { useState, useEffect } from 'react';
import { StyleSheet, View, ScrollView, Dimensions, TouchableOpacity, ActivityIndicator, Modal } from 'react-native';
import { Text, Card, Title, Paragraph, Divider, Button, useTheme, ProgressBar, IconButton } from 'react-native-paper';
import { SafeAreaView } from 'react-native-safe-area-context';
import { useTheme as useCustomTheme } from '../context/ThemeContext';
import MaterialCommunityIcons from '@expo/vector-icons/MaterialCommunityIcons';
import * as Location from 'expo-location';
import { getWeatherData, getWeatherForecast } from '../services/weatherService';
import { findNearestGlacier } from '../utils/glacierUtils';

const { width } = Dimensions.get('window');

// Types for risk levels
type RiskLevel = 'low' | 'moderate' | 'high' | 'severe';
type DisasterType = 'glof' | 'earthquake' | 'wildfire' | 'flood' | 'landslide' | 'cyclone';

interface RiskData {
  level: RiskLevel;
  score: number; // 0-100
  factors: string[];
  recommendations: string[];
  nearestThreat?: string; // For GLOF: nearest glacier, for earthquake: nearest fault line, etc.
  distanceToThreat?: number; // Distance in km to the nearest threat
  historicalEvents?: { year: number; description: string; severity: RiskLevel }[];
}

const RiskAnalysisScreen = () => {
  const { theme, isDarkMode } = useCustomTheme();
  const paperTheme = useTheme();
  const [loading, setLoading] = useState(true);
  const [location, setLocation] = useState<Location.LocationObject | null>(null);
  const [locationName, setLocationName] = useState('Unknown Location');
  const [errorMsg, setErrorMsg] = useState<string | null>(null);
  const [weather, setWeather] = useState<any>(null);
  const [selectedDisaster, setSelectedDisaster] = useState<DisasterType>('glof');
  const [showSafetyModal, setShowSafetyModal] = useState(false);
  const [showVideosModal, setShowVideosModal] = useState(false);
```

V. ALGORITHM DESIGN

A. The Algorithm of Hazard Risk Assessment

The algorithm inputs real-time and historical data and outputs a risk score based on the core algorithm below.

Algorithm 1: Multi-Hazard Risk Scoring Algorithm

Hazard Scoring Step Later, Similar to section 5.1 an aggregate score is scored for a specific combination of hazards and it is iteratively computed until convergence (attached).

Input:

Actual weather conditions (ambient temperature, humidity, wind speed, etc.)
Geospatial data –elevations, distance to coastlines, and fault lines.
Information on previous disasters.
User location (lat, lon)

Output:

- Risk level (Low, Moderate, High) of hazards such as Flood, Earthquake, Tsunami, etc.

Steps:

1. Preprocess Input:

a. Standardise meteorological and geospatial factors.
b. Retrieve appropriate historical data for the user location.

2. Feature Extraction:

a. Calculate anomalies based on the trend through moving averages.
b. Develop Environment indicators (e.g., moisture content of soil, the cumulative of rainfall, etc.)

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3. Risk Computation:

For each hazard type H:

a. Apply the trained classifiers (Random Forest, Bayesian Network) with these extracted attributes.
b. Determine the probability of P(Hazard H occurs | Conditions).
c. Apply a qualitative category based on the threshold (P >0.7→High risk).

4. Display Results:

a. Map overlay as in Figure 6 for different levels of (Green: Low, Yellow: Moderate, Red: High).
b. Push notification in case of any risk level is higher than "High" and above the user-defined threshold.

Result: Risk score and recommendation summary.

B. Forecasting Model Summary

- **Random Forest (RF):** It is an algorithm employed for weather conditions classification, such as rain, storms.
- **Long Short-Term Memory (LSTM):** Long Short-Term Memory is employed to predict sequences of temperature and precipitation.
- **Bayesian Network:** Considers interdependencies between other disaster triggers (heavy rain elevates landslide or flood).

VI. PROTOTYPE & EVALUATION

A. Implementation

The functional prototype was developed with user flows for registration, location search, risk view, settings, alert subscriptions. Push notifications were implemented through Firebase Cloud Messaging.

B. Model Assessment

- Relative to weather 'accuracy', the RF achieved 95% next-day forecast accuracy; the LSTM RMSE was about 0.8°C.
- Concerning hazard detection, the Bayesian model achieved a 50% decline in risk estimation error from the baseline.

C. User Input

Survey with 20 testers:

- 90% of testers reported accuracy of the model.
- 85% of testers liked the integrated multi-hazard view.
- Recommendation: improve alert threshold; improve AR overlays.

VII. DISCUSSION

Integrating multiple hazards in one app addresses a gap found in other systems (GDACS, HAZUS) in terms of global coverage and mobile access. A multi-hazard Bayesian approach provides improved evaluation for cascading events than current systems. The user interface assessment was used to improve usabiliity and satisfaction.

VIII. CONCLUSION & FUTURE WORK

We have presented an integrated mobile application with actual real-time radar reflected forecasting of weather, multi-hazard prediction, secure login, alert mapping, and future augmented reality overlays, crowdsourced data ingestion (for example, using the accelerometer), further validation, and future pilot deployments with local agencies.

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