Flood Monitoring and Early Warning Systems – An IoTBased Perspective

Flood MonitoringusingSentinelSatelliteImages

Someoftheimagesdonotaddressthebimodaldistributi ontheory. The mountain shadows and the low backscatteringintensityvegetationcauseomissionsdu etosalt-and-peppernoiseandmisclassifications.Thiswasacknowle dgedintheyear 2020 during heavy inundations in the Yangtze Riverbasin of China. To address these issues, an improvisedflood mapping over the Otsumethod was proposed byChen and Zhao [32]. This isan automated flood- mappingtechniquethatcansolvetheissueofahigherse gmentationthreshold of images.The topological relationships and aDigital Surface Model (DSM) local search algorithm existon Google Earth Engine (GEE). The Sentinel-2 data hasbeen utilized to map vegetation and water areas and theSentinel-1 data was used in mapping floods using the Otsumethod.From the maps generated on the surface wateroccurrence,higheraccuracyof96.2and98.6%was achievedforplainsandterrain.Thefrequencyofapproxi mately0.5denotesthewaterregioninundatedrapidlywit

ahheavyrain.Thevalueoffrequencyofapproximately1 repr esentsthepermanentwaterregionandthe lower frequency represents the affected area. The timerequired to download data and storage could be drasticallyreducedbythedeploymentofthefloodmappin galgorithm.Yetthereareafewlimitationsofthismethod.T hemisclassificationwasaddressedby theimmediacy and coarse resolution of Advanced Land Observing Satellite'GlobalDigitalSurfaceModel(ALOSDSM)data. However, higher tolerance must be set due to the ALOSDSMaccuracy.Additionally,monitoringnarrowa ndsmaller rivers or lakes is limited in Sentinel-1 images dueto theresolutionandimagingmode.

Xue et al. proposed the Sentinel image'snormalizeddifferencefloodindex(NDFI)withthesum merpermanentwaterbodies(SPWB)basedNDFI- SPWBframework[33].This framework aims tointerpret the flood maps visuallyanddecidethemisclassificationandomission s.Thisframework extracts the damages caused in the flood-proneregionusing NDFI and identifies thefloodedarea.Toidentify the range of SPWB, the probability of waterareaisdetectedthroughacombinationofmultipleremo tesensing indexes. Further, the initially extractedresults areoptimizedusingtheSPWBexclusionlayer.Thecalc ulation ofNDFIisdoneusing theformula:

$$NDFI = \frac{\mathrm{mean}\,\sigma0(\text{"reference"}) - \mathrm{min}\,\sigma0(\text{"reference+flood"})}{\mathrm{mean}\,\sigma0(\text{"reference"}) + \mathrm{min}\,\sigma0(\text{"reference+flood"})}. \quad (1)$$

Where,themean("reference")isconsideredasanaverage against the min ("reference + flood") which is theminimumvalueoftheimagepixel'sbackscattercoefficient. The picture component when less than -1 ormore than 0 is the outlier to be removed. This willensurethe consistency and accuracy of the results. The thresholdiscalculated using:

$$th = mean(NDFINNlood) - k * std(NDFINNloo). \quad (2)$$

Where,thisthethreshold,std(NDFIflood)isthestan dard deviation, and mean (NDFIflood) is the averagevalueofthedifferenceimage.Basedonthepro posedframeworkwithnoescalationinomissionerror,t heoverallaccuracyisimprovedwithnochangeinprodu ceraccuracywhereastheuseraccuracyincreasedby10 %andtheKappacoefficient increased by 0.08approximately. The sourceforflooddataisalsoavailableasGlobalFloodMonitoring(GFM)from Copernicus Emergency ManagementService(CEMS).ItisarobustsetupthatusesSARdatafo rmonitoringfloodsgloballyandnearreal- time(NRT)monitoring. By using a local parameterwith precipitation,theSARimageryisclearlydistinguishedf orclassifiedandunclassified data. The process is based on an enhancedglobal data-cube algorithmstructure with harmonic time-series analysis. Thisis an integrated component of GFM.Theunresponsive regions and observations arefeaturedexclusively. The Bayes classification decision engine thatworks on this algorithmexecutes faster during near real-timefloodmapping[34].

4.1. FloodMonitoringwiththeIntegrationofI o TTechniquesUsingSatelliteImages

Anensemblemodel hasbeenproposedbyM.Khalafet al. [35]thattheuseofvariousMLalgorithmswithIoT sensor data is a reliable method of predicting the water levelsseverity.Automatedanalysisofpreviously storedi nformationcanbewellutilizedintheearlypredict ionand preventdisasters.Asetof11attributesfromsens ordata was analysed using the long short-term memory (LSTM)algorithm. The ensemble LSTM classifier data accuracycontributed towards the detection of water level severity.An IoT-enabled flood severity prediction model is shownin Figure5.

ProposedFrameworkfortheNewFloo d Monitoring and Early WarningSystem

ThedevelopmentofanewFMEWSsystemwithi ntegrati on of SAR images implements image processingonSentinel-Iimagesis proposed.Additionally,anIoTsensors-based modulethat detects inundation levels wouldbeamoreappropriateapproachforidenti fyingflo odprone

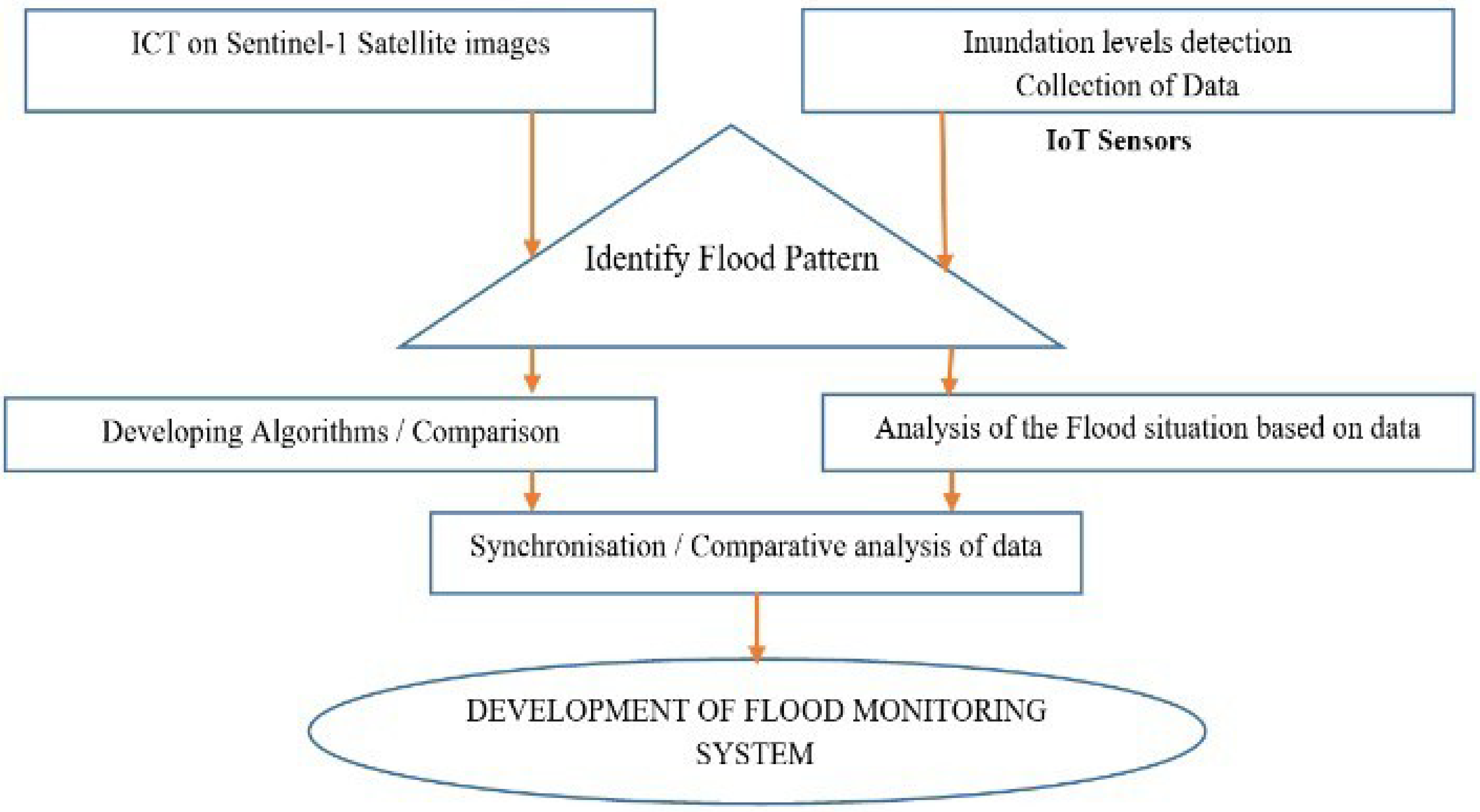

Figure5.IoT-basedfloodmonitoringandearlywarningsystem (FMEWS)

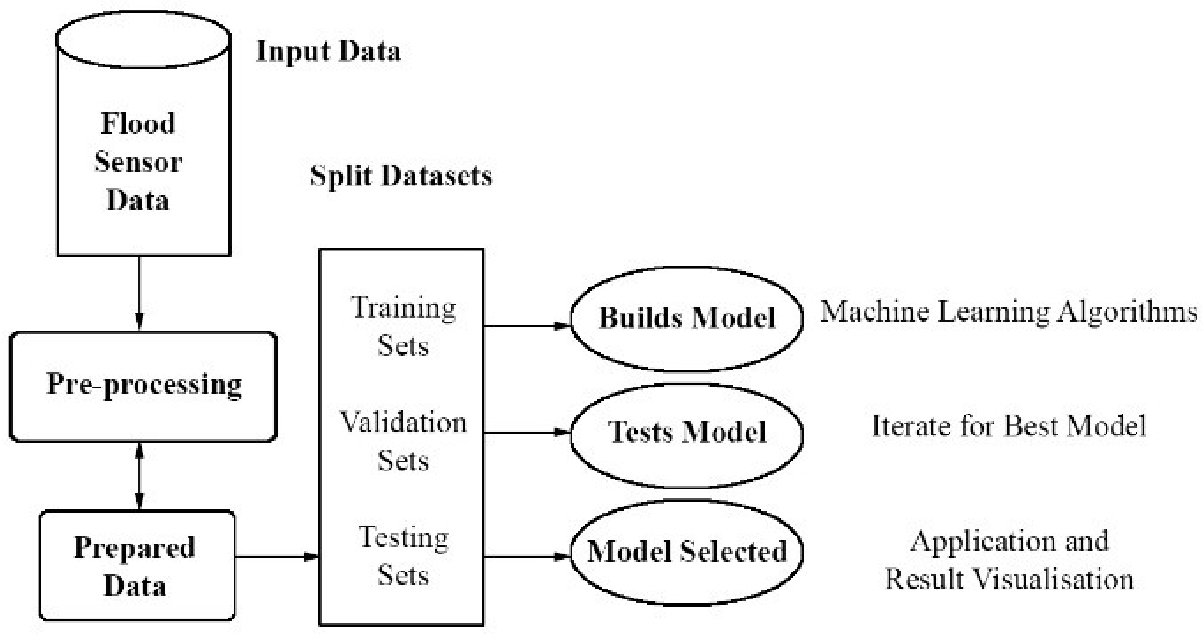

Figure 5. IoT-Enabled
IoT-Enabled
Flood Severity Prediction
viaEnsembleMLModels[35]

areas and comparing them with the SAR processed imagesforaccuracy.Thisisexpectedtoguideth edecisi on-makingauthorities in taking precautionary measures accordingly.Eventually, the use of ML algorithms and the integrationofIoTsensordataandsatelliteimage sforflo odmonitoringwould be an ideal way forward toachieve accurate, multi-variance data-based outcomes to analyze and evaluate theefficiencyofprocesses.TheproposedIoT-basedfloodmonitoring and early warning system(FMEWS) is shownin Figure6.

All methods have different techniques for performanceevaluationandusedifferentmetr icstoev aluatetheeffectiveness of relevant approaches. The use o f variousMLalgorithmsasanewapproachthatcan befoll owedwillalsoinvolveexploringandimplement ingopti mizationtechniques by utilizing swarm optimization and geneticalgorithms along with the use of IoT Sensors will alwaysbe an added advantage. The proposed SAR module wouldbe supported by change detection techniques and the IoTsensor-basedmoduleusesSARinterferometrydatafur ther paving the way for effective comparative analysis and anenhanced outcome. The system will help in evaluating thequality of service based on the results generated.Further,usingthisintegratedsystem cangre atlyinfluencethedecisionmakingofrelevantauth orities to mitigatethefloodsintheconcernedareasandsa feguard lifeandproperties.Theproposedframeworkcan beimpr ovedfurther to address other potential risks such as landslidesand emergency mapping support during earthquakes. Theresearchers should explore different ways with a strongcommitment to studyclimate change and its impact basedon data from hydrological, meteorological, and satellite-basedinformation.Thiswouldhelpinmeasuringt heinun dation levels across different regions and addresstheissues accordingly.

5. Conclusion

IoT sensors-based flood monitoring systems tend to belower cost, consistent and portable. However, when thereare large areas, these systems are notrecommended due tothe fact that every sensor is generally invigorated by avitalityrestrictedbattery.Thispaperreviewed a ndclarifi eddifferentecologicalandfloodmonitoringsys temsan dvariouscommunicationtechnologiesthatsupp ortenh ancing the detection of viable floods and identifyingcautioning issues. Further, these systems that are havinghighly reliable sensors with powerfulIoT cloud platformscanbefundamentallyutilizedforlarge-scaleenvironmentalmonitoring,andfloodpredi ctionan dpreventdamagecausedbyit.Eventhoughthem from flood-proneareasanddeveloprobustandsecureFloodmo nitori ngand early warning system.

Declaration

This manuscript has not been submitted to, nor is underreviewat, anotherjournalorotherpublishingvenue.

ethodology of utilizing IoT in flood monitoring is notextensively explored at this point, we will see a colossalutilization of IoT and some new advancements in the nearfuture. For example, AI and5G techniques meet up for thepredictionoffloodsaswellasothernaturalcala mities. Theuseofsatelliteimagescouldbeveryhelpfulin floodm onitoringas theyhelptokeepan eyeonthewaterbodiesandthechangeintheirbe haviourf romabove.Someresearchers have utilized databased on Google Maps tobuildadetectionmodel.GSMmodulesalsoha vebeenu sedindifferentwayssimilarly.Closeconsultatio nwithhy drologistsandlearningmachine-learningalgorithmscanfurthersupportbuildingeff icient monitoringandalertsystem. In the future, the usageof SAR data from theSentinal-1satelliteisanaddedadvantageinhandlingresc ue operations and damage assessments based on databefore and after floods. The wireless sensors can help ingatheringflood relateddata bycreating a database forfurtheranalysis.Asarecommendation,therei satrem endous opportunity to explore the combination of IoTsystems and SAR data to classify the images

Acknowledgements.

TheauthorsarethankfultotheAdvancedComputingResearchLaboratory,DepartmentofComputerApplication, Integral University, Lucknow for providingthe necessary support to carry out this research. This workissupportedbytheIntegralUniversityunder GrantI UL/IIRC/SMP/2023/016.

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