**Flood Monitoring and Early Warning Systems – An IoT Based Perspective**

# Flood MonitoringusingSentinelSatelliteIma ges

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 Otsu method was proposed byChen and Zhao [32]. This is an 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.Thevalueoffrequencyofapproximately1repr 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’s normalizeddifferencefloodindex(NDFI)withthesum merpermanentwaterbodies(SPWB)basedNDFI- SPWBframework[33].This framework aims to interpret the flood maps visuallyanddecidethemisclassificationandomission s.Thisframework extracts the damages caused in the flood-proneregionusing NDFI and identifies the floodedarea.Toidentify the range of SPWB, the probability of water areaisdetectedthroughacombinationofmultipleremo tesensing indexes. Further, the initially extracted results areoptimizedusingtheSPWBexclusionlayer.Thecalc ulation ofNDFIisdoneusing theformula:

𝑁 𝐷 𝐹 𝐼

=meanσ0(“reference”)−minσ0(“reference+flood”).(1)

meanσ0(“reference”)+minσ0(“reference+flood”)

Where,themean(“reference”)isconsideredasanav erage against the min (“reference + flood”) which is theminimumvalueoftheimagepixel’sbackscattercoe fficient. The picture component when less than -1 ormore than 0 is the outlier to be removed. This will ensurethe consistency and accuracy of the results. The thresholdiscalculated using:

𝑡 ℎ=𝑚 𝑒 𝑎 𝑛 (𝑁 𝐷 𝐹 𝐼 𝑁 𝑁 𝑙 𝑜 𝑜 𝑑 )−𝑘 ∗𝑠 𝑡 𝑑 (𝑁 𝐷

𝐹 𝐼 𝑁 𝑁 𝑙 𝑜 𝑜 ).(2)

Where,thisthethreshold,std(NDFIflood)isthestan dard deviation, and mean (NDFIflood) is the averagevalueofthedifferenceimage.Basedonthepro posedframeworkwithnoescalationinomissionerror,t heoverallaccuracyisimprovedwithnochangeinprodu ceraccuracywhereastheuseraccuracyincreasedby10

%andtheKappacoefficient increased by 0.08 approximately. The sourceforflood dataisalsoavailableasGlobalFloodMonitoring(GFM) from Copernicus Emergency Management Service(CEMS).ItisarobustsetupthatusesSARdatafo rmonitoringfloodsgloballyandnearreal- time(NRT)monitoring. By using a local parameter with precipitation,theSARimageryisclearlydistinguishedf orclassifiedandunclassified data. The process is based on an enhancedglobal data-cube algorithm structure with harmonic time-series analysis. This is an integrated component of GFM.The unresponsive regions and observations are featuredexclusively. The Bayes classification decision engine thatworks on this algorithm executes faster during near real-timefloodmapping [34].

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# FloodMonitoringwiththeIntegrationofIo TTechniquesUsingSatelliteImages

Anensemblemodel hasbeenproposedbyM.Khalafet al. [35]thattheuseofvariousMLalgorithmswithIoTsensor data is a reliable method of predicting the water levelsseverity.Automatedanalysisofpreviouslystoredi nformationcanbewellutilizedintheearlypredictionand preventdisasters.Asetof11attributesfromsensordata

# ProposedFrameworkfortheNewFlood Monitoring and Early WarningSystem

ThedevelopmentofanewFMEWSsystemwithintegrati on of SAR images implements image processingonSentinel-limagesis proposed.Additionally,anIoTsensors-based module that detects inundation levels wouldbeamoreappropriateapproachforidentifyingflo odprone

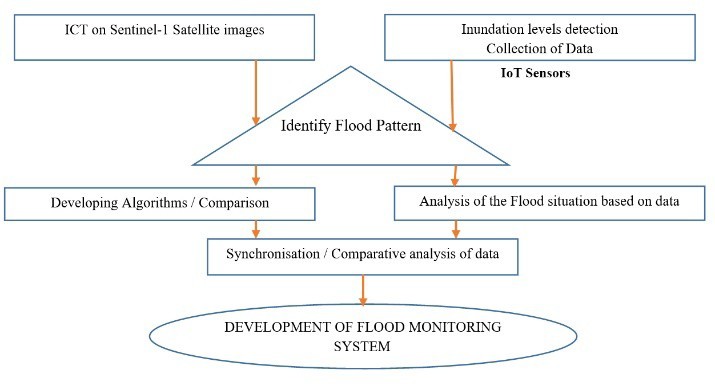
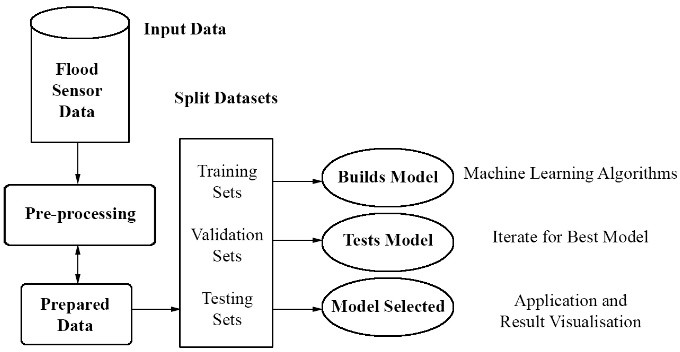


Figure5.IoT-basedfloodmonitoringandearlywarningsystem(FMEWS)

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.



IoT-Enabled IoT-Enabled Flood Severity Prediction viaEnsembleMLModels[35]

Figure 5.

Figure 5.

areas and comparing them with the SAR processed imagesforaccuracy.Thisisexpectedtoguidethedecisi on-makingauthorities in taking precautionary measures accordingly.Eventually, the use of ML algorithms and the integrationofIoTsensordataandsatelliteimagesforflo odmonitoringwould be an ideal way forward to achieve 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 performanceevaluationandusedifferentmetricstoev aluatetheeffectiveness of relevant approaches. The use of

variousMLalgorithmsasanewapproachthatcanbefoll owedwillalsoinvolveexploringandimplementingopti 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- basedmoduleusesSARinterferometrydatafurther

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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,usingthisintegratedsystemcangre atlyinfluencethedecisionmakingofrelevantauthorities to mitigatethefloodsintheconcernedareasandsafeguard lifeandproperties.Theproposedframeworkcanbeimpr ovedfurther to address other potential risks such as landslidesand emergency mapping support during earthquakes. Theresearchers should explore different ways with a strongcommitment to study climate change and its impact basedon data from hydrological, meteorological, and satellite- basedinformation.Thiswouldhelpinmeasuringtheinun dation levels across different regions and address theissues accordingly.

from flood-

proneareasanddeveloprobustandsecureFloodmonitori ngand early warning system.

Declaration

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



5. Conclusion

IoT sensors-based flood monitoring systems tend to belower cost, consistent and portable. However, when thereare large areas, these systems are not recommended due tothe fact that every sensor is generally invigorated by avitalityrestrictedbattery.Thispaperreviewedandclarifi eddifferentecologicalandfloodmonitoringsystemsan dvariouscommunicationtechnologiesthatsupportenh ancing the detection of viable floods and identifyingcautioning issues. Further, these systems that are havinghighly reliable sensors with powerful IoT cloud

platformscanbefundamentallyutilizedforlarge- scaleenvironmentalmonitoring,andfloodpredictionan dpreventdamagecausedbyit.Eventhoughthemethodol ogy 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 and 5G techniques meet up for thepredictionoffloodsaswellasothernaturalcalamities. Theuseofsatelliteimagescouldbeveryhelpfulinfloodm onitoringas theyhelptokeepan eyeonthewaterbodiesandthechangeintheirbehaviourf romabove.Someresearchers have utilized data based on Google Maps tobuildadetectionmodel.GSMmodulesalsohavebeenu sedindifferentwayssimilarly.Closeconsultationwithhy drologistsandlearningmachine- learningalgorithmscanfurthersupportbuildingefficient monitoringandalertsystem. In the future, the usage of SAR data from theSentinal- 1satelliteisanaddedadvantageinhandlingrescue operations and damage assessments based on databefore and after floods. The wireless sensors can help ingatheringflood relateddata bycreating a database forfurtheranalysis.Asarecommendation,thereisatrem endous opportunity to explore the combination of IoTsystems and SAR data to classify the images

Acknowledgements. TheauthorsarethankfultotheAdvancedComputingRe searchLaboratory,DepartmentofComputerApplicati on, Integral University, Lucknow for providingthe necessary support to carry out this research. This workissupportedbytheIntegralUniversityunderGrantI UL/IIRC/SMP/2023/016.

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