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Research Article

Advanced Hydrological Simulation and Hybrid CNN-LSTM Models for Sustainable Water Resource Management in Nepal

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Nepal's diversified terrain and vast watershed create both opportunities and obstacles for water resource management. Conventional methods frequently fail owing to insufficient data, old methodologies, plus a lack of compatibility with modern technology. To solve these issues, the research suggests using improved hydrological simulation and sophisticated models for forecasting for sustainable water resource management in Nepal. The study uses cutting-edge technology, such as satellite imagery, Geographic Information Systems (GIS), with neural networks, to create a new combination CNN-LSTM technique. Hydrological statistics regarding precipitation, river flow, and glacial melt, as well as meteorological, geographical, and socioeconomic information, was gathered then filtered. This data integration enhances the accuracy of models, providing real-time monitoring and prediction capabilities. The hybrid CNN-LSTM system incorporates the qualities of Convolutional Neural Networks with collecting time properties from images, CatBoost for dealing with tabular information and spatial traits, with LSTM for enhanced classification of images and sequence data processing. The suggested model beats previous techniques, with an estimation accuracy of 99.20% to identify hydrologic occurrences. The incorporation of these latest innovations enhances floods projections, famine projections, and general handling of water techniques. This study shows that sophisticated hydrological simulations may considerably improve the durability and long-term viability of the management of water resources in Nepal, making it a valuable tool for regulators and managers. The research results call for bigger investments in the internet, training, and the creation of favorable regulations to assure the long-term sustainability of these programs. By tackling the constraints of existing approaches and adopting creative approaches, Nepal may accomplish responsible management of water resources while ensuring the availability of water and increasing the standard of life over its people.

Keywords: Hydrological Simulation, CNN-LSTM Hybrid Model, Water Resource Management, Real-Time Monitoring, Flood and Famine Projections

1. INTRODUCTION

Nepal's diversified terrain and vast watershed present distinct challenges and possibilities for water resource administration [1]. The nation has been blessed with considerable bodies of water, such as significant streams, rivers, and glacier savings, which make it among the most water-rich countries. But adequate oversight of these assets is essential for ensuring equitable growth, mitigating catastrophic events, other meeting agricultural, commercial, and domestic requirements [2]. Modelling of waterways is essential for knowing and handling the supply of water [3]. These simulations replicate the entire cycle of water, encompassing rain, penetration, rainfall, and evaporated water, which aids in predicting the supply of water and danger of flooding. In the nation of Nepal [4], wherein the monsoons and the melting of glaciers have significant effects on water flow, comprehensive hydrological simulation is critical for effective water administration [5]. Conventional water administration systems in Nepal frequently suffer with insufficient information, obsolete methodologies, and inadequate incorporation of modern technology. These constraints impede the capacity to reliably predict hydrological phenomena and efficiently administer the availability of water, resulting in challenges such as shortages of water, wasteful irrigation methods,[6] as well as a greater susceptibility to extreme weather conditions. The combination of cutting-edge technology such as satellite imagery, Geographic Information Systems, and algorithms for learning creates new prospects for modelling of waterways. Such devices can give real-time data [7], enhance accuracy of forecasts, and provide improvements in utilization of water resources by combining different sources of data and approaches to analysis. GIS and remote sensing are critical technologies for gathering and interpreting geographical and time-based information about water resources [8]. Satellite imaging and applications for geographic information systems can track shifts in the utilization of land, bodies of water, and patterns of rainfall, giving useful data for modelling hydrology [9].

In Nepal, such tools can be used to map watersheds, evaluate dangers of flooding, and measure melting glaciers and flow of rivers [10]. Data analytics and machine learning have the potential to greatly improve hydrodynamic model predictability [11]. Algorithms using machine learning can enhance drought and flooding predictions, as well as irrigation techniques, by evaluating previous data and recognizing similarities. These techniques can also aid in the most effective use of water resources while guaranteeing that their resources are utilized successfully and responsibly [12]. For instance, in some areas, the combination of imagery from satellites with machine learning algorithms has resulted in more precise floods forecasts, allowing for prompt evacuations and lowering the effect of flooding on populations [13]. The Nepalese government, in collaboration with other nations and governmental organizations [14], has come to understand the value of sophisticated hydrological simulation and started a number of projects to improve the management of water resources [15]. Regulations that encourage the use of new technologies, strengthening capacities, and global cooperation are critical to the successful completion of these projects. Future research in modelling hydrology needs to concentrate on enhancing its precision and expansion, incorporating additional information from various sources, and creating accessible resources for planners and clinicians [16].

Cooperation among investigators, engineers, as well as managers of water resources is critical for addressing Nepal's complex water-related concerns. Effective groundwater conservation in Nepal necessitates an integrated strategy that incorporates extensive mathematical modelling with cutting-edge technology [17]. By tackling the constraints of existing approaches and implementing novel ideas, Nepalese may improve its water resource management practices, assure the availability of water, and strengthen resistance to hydrologic anomalies [18]. This comprehensive strategy would promote equitable growth while enhancing the standard of life of Nepal's people [19]. Climate change has a huge impact on hydrologic cycles around the world, including Nepal. Temperature rises accelerate glacier melt and modify precipitation patterns [20], resulting in greater severity and frequency of flooding including floods [21], landslides, and drought. These modifications need the use of modern hydrological simulations capable of accounting for variations in the climate and providing accurate projections for optimal governance of water resources [22]. Nepal's agricultural and native ethnic groups have extensive oral tradition regarding regional water assets and utilization strategies [23]. Combining conventional understanding with current hydrological modelling can improve the accuracy and usefulness [24]. The combination of these methods can result in more culturally relevant and practical environmental solutions, assuring public acceptance and long-term execution [25].

Sophisticated hydrological simulations not just enhance water resource management, but they also help communities become more resilient to catastrophic events. These simulations allow populations to better plan ahead and react to hydrologic catastrophes by offering notification systems and precise forecasts, resulting in fewer deaths and property damage [26]. Training and educational initiatives are critical for ensuring that local people comprehend and utilize these new technologies. Training and development of capabilities are critical for the successful deployment of modern hydrological projections in Nepal [27]. Training initiatives for politicians, scientists, technicians, and local communities in the usage and analysis of these representations are essential. Developing regional capacity allows Nepal to assure the continued viability and universality of these technologies, resulting in long-term gains in the control of water resources [28]. Collaborative research and development initiatives among Nepalese universities and foreign organizations have the potential to speed up the advancement of hydrological simulation technology [29]. Combining expertise, data, and assets can result in the creation of stronger and complete simulations. Worldwide partnership can also help to transfer knowledge and technology [30], thus improving Nepal's ability to cope with its specific water shortage concerns.

Securing enough investment and funding is critical for the development and implementation of sophisticated hydrological models [31]. Governments, foreign funders, and private-sector players have to prioritize investment in managing water resources technology. The financing should include not just the initial implementation of these technology [32], but additionally regular upkeep, developments, and building capacity efforts. Appropriate regulatory and policy structures are required to facilitate the use of improved mathematical models for hydrology [33]. Policies should support the adoption of innovative technology, data exchange, and the establishment of water resource administration standards. The regulatory structures ought to include data privacy, creativity, and the incorporation of conventional wisdom [34].

Continuous monitoring and evaluation of mathematical models and methods for managing water is required to ensure their efficacy and flexibility [34]. periodic evaluations can help discover areas for enhancement, monitor advancement, and give evidence for policy changes. Providing explicit indicators of achievement and metrics will assist drive the models towards continuing development and improvement. Increasing the general awareness of the significance of sophisticated computational hydrology and efficient utilization of water resources is critical [35]. Public events can help residents understand the positive effects of these advances and how they improve general community well-being. Involving people in water-related activities can develop an awareness of responsibility and accountability, resulting in more efficient and environmentally friendly solutions [36]. A long-term goal for environmentally friendly water utilization in Nepal necessitates a dedication to ongoing creativity and enhancement. Using sophisticated hydrological simulations and modern equipment is a step toward achieving this aim [37]. Nepal can accomplish optimal conservation of water resources, improve its adaptation to climate change, and assure a prosperous future for its people by cultivating a creative way of life, participating in education and capacity constructing, and encouraging collaboration [38]. The key contributions of this article are,

- Combines satellite imagery, GIS, and neural networks for comprehensive data collection and analysis in hydrological modelling.
- Utilizes Generative Adversarial Networks to enhance dataset robustness and diversity, improving model performance.
- Develops a CNN-LSTM model that integrates spatial and temporal data for accurate hydrological event prediction, achieving 99.20% accuracy.
- Implements and validates models like SWAT and HEC-HMS, ensuring reliable simulations and predictions of hydrological processes.
- Facilitates real-time environmental monitoring and accurate forecasting of floods and famines through cutting-edge technologies, supporting effective water resource management.

The paper is structured as follows: Section 2 comprises relevant material designed to help readers comprehend the proposed paper using existing methodologies, while Section 3 elaborates on the problem description. The fourth component displays proposed CNN-LSTM methodology. Section 5 includes tabular and graphical representations of the results and performance indicators and at last in Chapter 6, the conclusion and future works are discussed.

2. RELATED WORKS

The increasing challenges of water pollution and global warming have necessitated innovative approaches for environmental monitoring and management worldwide [1]. Current study emphasizes the efficacy of networked sensors and artificial intelligence in applications in the environment. For example, networks of sensors based on ESP32 and TensorFlow Lite have been utilized for immediate information collecting and processing, improving the precision and rapidity of outside surveillance. Research have shown that combining these innovations with aircraft for applications such as water-based disposal can considerably increase efficiency and coverage. The inclusion of GSM module such as SIM800L for remotely notifications improves the responsiveness of these systems by sending users timely information regarding surroundings such as trash level and the quality of water. Ultrasonic devices are well-known for their accuracy in detecting water levels, which helps in mapping floods and monitoring. Artificial intelligence models, especially Inception-v3, have exhibited outstanding performance in identifying among clean and filthy water, with estimated precision of up to 97% in test settings. These improvements highlight the promise of merging artificial intelligence, algorithms for learning, and IoT technology to develop robust as well as proactive infrastructure for controlling water resources and conservation. The suggested approach, which incorporates such technologies, represents an important step toward long-term management of water resources by offering real-time monitoring, effective garbage collection, and reliable alerting capabilities, as demonstrated by the creation and testing of a working model for potential installation in regions affected by flooding.

The Hindu Kush Himalayan region's vulnerability to periodic monsoon floods necessitates effective early warning systems to safeguard millions of residents [2]. The research emphasizes the crucial relevance of enhanced hydrologic prediction technologies in reducing the likelihood of flooding. SERVIR-HKH and NASA-AST created and set up two well-known online flood prediction systems, ECMWF-SPT and HIWAT-SPT, to meet this demand in Bhutan, Bangladesh, and Nepal. ECMWF-SPT gives a unified prediction with a delay of up to 15 days, whereas HIWAT-SPT offers determinate forecast with a 3-day lead time, encompassing almost all rivers in the entire area. The inclusion of hydrological simulations into prediction validation procedures is critical for improving systems for forecasting and evaluating the precision of predictions. Existing research emphasizes the significance of verifying forecast models to assure their accuracy and dependability. The validation procedure evaluates the efficacy of such systems using both stochastic as well as mechanistic measures, as well as visualizations. Experimental proof shows that these kinds of models efficiently represent large flood occurrences, with tests conducted across various places suggesting strong predictive accuracy and prediction dependability. The aforementioned body of work focuses on advances in flood projection methods and their crucial impact on strengthening early warning systems, resulting in better response and preparation methods in areas at risk of flooding.

The promotion of Climate-Resilient Water Management (CRWM) in South Asia hinges on the availability and utilization of high-quality climate information, which is pivotal for designing and implementing effective interventions [4]. The research stresses the necessity of incorporating complete climate data, such as factors, dynamics, and outputs from multiple climate models, into the administration of water resources plans. The Action Coalition on Climate Today initiative, which is supported by the UK Ministry for Foreign and Commonwealth Affairs, exhibits this strategy. Since 2014, ACT has worked with national and subnational governments in five South Asian nations to improve environmental adaption strategies and implementation. Studies illustrate the distinction across CRWM and classical water management, emphasizing the importance of precise climatic knowledge in developing adaptable solutions. The initiative's activities have yielded helpful insights into how climate knowledge might guide water-related actions and policies. accessibility, significance, and incorporation into decisions are among the difficulties associated with data on climate use. ACT's programs showcase a wide range of climate information uses, from policy development to on-the-ground adaption projects, highlighting the possibility of personalized climate data in improving CRWM. This collection of work demonstrates the need of eliminating hurdles to the efficient use of climate information to guarantee stable and environmentally friendly water-related procedures, as well as providing practical direction to project architects and implementers on how to use climate data to drive efforts to adapt.

The intersection of climate change and digitalization has emerged as a crucial area of focus, with significant implications for adaptation and mitigation strategies worldwide [6]. The research emphasizes the growing intensity and incidence of severe storms, which jeopardize water and food security, worsen impoverishment, and endanger agriculture supply networks and coastal towns. The Latin America and Caribbean (LAC) area illustrates these weaknesses, as it faces a slew of climate-related difficulties including glacier flee, flooding, avalanches, and storms, which greatly affect the poor. Notwithstanding these hurdles, LAC has led the way in developing novel climate policies, such as taxing carbon in Mexico and environmentally friendly forestry in Brazil, which have enormous mitigating capacity. Integrating temperature risk handling into government is critical for emerging nations in reacting effectively to climatic shocks, which necessitates rapid and detailed reporting. The introduction of information and communication technologies (ICTs) and online platforms have transformed the environment monitoring and policy execution. Geographic information systems (GIS), remote sensing, broadband, wireless sensor networks, and the Internet of Things (IoT) are all useful tools for environmental monitoring and handling emergencies. Case examples demonstrate the importance of collaboration between the public and private sectors in implementing ICTs for climate adaptation and mitigation, while emphasizing the need for a multi-stakeholder approach. Furthermore, the research investigates the environmental effects of rising ICT use and the greening of these advances. This collection of work emphasizes the transformative impact of ICTs in tackling climate change, arguing for thorough governmental regimes to properly use these tools.

The Himalayan region's susceptibility to natural disasters, particularly flash floods and landslides, is exacerbated by its complex topography and climatic variations [9]. The research emphasizes the importance of the environment and topographical conditions in determining flash flood episodes, as seen in Uttarakhand's Nainital region. Pre-flood parameters such as aerosol optical depth, cloud cover thickness, and water vapor levels have all demonstrated substantial relationships with flood incidents, as evidenced by the October 2021 episodes, which varied from the regular June to September trend, implying potential climate changes. Robust statistical techniques, such as the Autocorrelation is function, Mann-Kendall tests, and Sen's slope Estimator, were used to examine the precipitation trends over two decades, indicating generally small changes, with the exception of a noticeable drop in July. The combination of sensors and data from satellites, such as Meteosat-8, has been critical for comprehending flash flood processes and guiding disaster preparedness methods. Studies highlight the importance of excellent quality hydrological modelling, particularly the use of tools such as the Soil and Water Assessment Tool (SWAT), in successfully handling water resources in such hard terrains. This is consistent with Patel et al.'s (2022) study on the 2013 Uttarakhand floods, which emphasizes the necessity of precise hydrologic evaluations and effective disaster-management techniques. The research emphasizes the importance of harnessing enhanced geospatial information alongside immediate tracking to improve resilience and mitigate the financial repercussions of floods and storms in mountainous areas.

The sensitivity of hydrological systems to climate change and their crucial role in the environment have driven extensive research into the impacts of climate change on hydrology [10]. The research highlights that predicting such effects is a multi-stage process with inherent ambiguity. Uncertainty come from a variety of factors such as the environment situation choosing, GCM efficiency, scaling down techniques, prejudices in downscaled information, mistakes in hydrological models inputs, and and fundamental and a parametric unknowns within hydrology models. For instance, future climatic scenario uncertainties are predicted to be less severe than those related to GCM decision. A multi-model ensembles strategy is suggested to more accurately account for GCM-related unpredictability, and taking advantage of a variety of climatic forecasts is more successful than depending on an individual scenario. For region research, GCMs must be downscaled using statistics or dynamic techniques, such as regional climate models (RCMs), and bias correction can improve RCM estimates greatly. Evaluating the model's efficiency on a national level is critical for creating viable adaptation plans. A comprehensive evaluation of uncertainty at each level of environmental impact investigations on hydrological is crucial for developing strong plans for adaptation, emphasising the importance of precise scientific techniques in hydrology research on effects of climate change.

The SERVIR program, a collaborative initiative between NASA and USAID, exemplifies the integration of satellite data to address critical global challenges in food security, agriculture, water resources, land use, and climate [14]. SERVIR has worked on behalf of stakeholders in 50 countries, partnered with 390 institutions, and created over 70 products from 27 spacecraft and instruments over the last fourteen years, while also teaching about 7,400 observation professionals. SERVIR began as an incubation for Earth-based science and has since grown into a collaboration paradigm that encourages South-South and North-South partnerships to build new, scalable technologies. Its driven by demand strategy prioritizes the establishment and implementation of spatial services, as seen by the 2016 development of the 'SERVIR Program Development Toolkit', which has since inspired other observation programs. The Service Catalogue was launched in 2019 to facilitate access to these services and demonstrate SERVIR's dedication to practical, long-term geospatial data uses. Applying hubs, such as SERVIR-West Africa, SERVIR-Eastern & Southern Africa, SERVIR-Hindu Kush Himalaya, SERVIR-Mekong, and SERVIR-Amazonia, ensure localized expertise and impact while reflecting SERVIR's global reach and ability to adapt for dealing with climate change issues using revolutionary space-based and geographic information system technology.

The literature underscores the critical importance of surface water monitoring and extraction in regions like Nepal, where rivers and lakes are vital but increasingly threatened by human activities and climate change [16]. Despite the availability of cutting-edge remote sensing technologies and open-source data, thorough surveillance attempts have been restricted. Recent study has investigated a variety of strategies for improving the surface water extraction accuracy, including single or multiple water index methods and, more recently, artificial intelligence algorithms. Machine learning techniques such as Naive Bayes, recursive partitioning and regression trees, neural networks , support vector machines , random forest , and the gradient boosted machines have all produced results that are encouraging, especially when backup bands that such just like slope, NDVI, and NDWI are included. In Nepal's various landscape, which includes hilly regions, flatlands, and the Himalayas with snow and shadows, algorithm performance fluctuates, but RF consistently displays high accuracy and Kappa values. Studies indicate that algorithms be tailored based on altitude and climate variables, with the inclusion of specific bands or terrain information to improve extraction accuracy, hence providing to enhanced water management techniques in regions of vulnerability such as Nepal.

The literature highlights the transformative impact of flood forecast models, driven by advancements in scientific research and the application of machine learning (ML) techniques [17]. Flooding prediction has advanced tremendously, helping to reduce flood risks, formulate educated policies, and mitigate human deaths and damage to property around the world. Scientometric analysis has helped discover major trends and developments in flood research by using citation-based data to bring attention to important phrases, top papers, highly cited journal articles, important nations and leading authors in the area. ML techniques including choice trees, neural networks with artificial intelligence (ANNs), and wavelet neural networks (WNNs) have become popular as effective tools for improving predicting algorithms. These methods are evaluated in terms of accuracy, speed, and efficacy, providing climate scientists and specialists with useful insights into which machine learning algorithms are best suited for various forecasting jobs. Nations prone to catastrophic flooding, such as India, China, Nepal, Pakistan, Bangladesh, and Sri Lanka, could benefit significantly by employing these advanced flood estimate gets closer highlighting the critical role of machine learning-driven advancements in alleviating the catastrophic implications of floods around across the globe.

Pollution of the water supply and warming temperatures demand novel environmental monitoring techniques that combine networks of sensors and machine learning for improved precision and effectiveness. ESP32 with TensorFlow Lite, drones, GSM modules (SIM800L), and ultrasonic equipment all contribute to real-time data capture, rubbish disposal, and flood monitoring. The Inception-v3 model's great accuracy in water quality evaluation highlights the promise of these integrations. Sophisticated hydrology forecasting instruments, such as ECMWF-SPT and HIWAT-SPT, assist flood risk reduction in the Hindu Kush Himalayan area by providing ensembles and mechanistic predictions. Climate-Resilient Water Management (CRWM) in South Asia benefits from high-quality climate data, as evidenced by the ACT initiative. The convergence of the environment and digitization, particularly in LAC, highlights the use of ICTs in environmental monitoring. In the Himalayan region, disaster preparedness is informed by robust statistical studies and remote sensing. To resolve uncertainties, climate change effect studies on hydrology highlight the use of multi-model ensembles. The SERVIR initiative shows the use of satellite data to address global concerns, while modern sensors and machine learning improve surface water monitoring in Nepal.

3. PROBLEM STATEMENT

The increasing challenges of water pollution and global warming demand innovative solutions for environmental monitoring and management. Traditional methods often fall short in providing timely and accurate data, hindering effective response and mitigation strategies. The primary problems include inadequate real-time monitoring, inefficient waste collection on water surfaces [1], unreliable flood mapping, and poor water quality assessment. These problems can be addressed by installing sensor networks that use methods such as ESP32 with TensorFlow Lite for data processing in real time, incorporating drones for improved garbage pickup efficiency, utilizing GSM modules such as SIM800L for timely remote alerts, and installing ultrasonic detectors for precise level of water identification. Furthermore, algorithms using machine learning such as Inception-v3 can considerably increase the surveillance of water quality accuracy. This strategy seeks to build strong, reactive systems for the oversight of water resources and environmental protection, bridging significant gaps in present approaches and results in long-term, constant surveillance, effective disposal of garbage, and dependable alerts regarding floods [1].

4. PROPOSED CNN-LSTM METHODOLOGY

The proposed methodology for enhancing water resource management in Nepal leverages advanced hydrological simulation and sophisticated forecasting models, integrating cutting-edge technologies such as satellite imagery, Geographic Information Systems , and neural networks. This involves collecting diverse hydrological data, including precipitation, river flow, glacial melt, and meteorological, geographical, and socioeconomic information from sources like government entities, research organizations, and satellite data providers. Data augmentation using Generative Adversarial Networks enriches the dataset, enhancing model robustness. The hybrid CNN-LSTM technique, combining Convolutional Neural Networks for spatial feature extraction and Long Short-Term Memory networks for temporal sequence processing, along with CatBoost for tabular data, improves prediction accuracy, achieving 99.20%

in identifying hydrologic events. Hydrological models like SWAT and HEC-HMS are calibrated and validated using historical data, ensuring reliability. The integration of remote sensing, GIS, and machine learning facilitates real-time monitoring and prediction, enhancing flood and famine projections, and overall water resource management. This methodology aims to address limitations of conventional approaches, providing sustainable and resilient water management solutions for Nepal, supported by policy recommendations for internet infrastructure, training, and regulatory frameworks. Figure 1 shows Proposed CNN-LSTM Methodology.

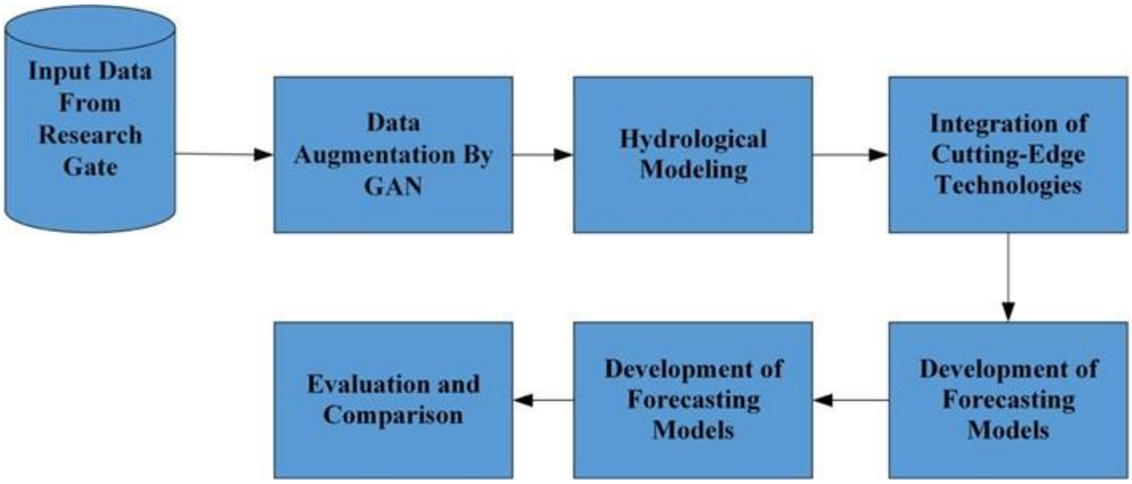

Figure 1: Proposed CNN-LSTM Methodology

4.1 Data Collection

Data acquired from Research Gate includes a wide range of datasets along with academic publications on water resource management and hydrologic simulation, which are critical for the Ganges, Brahmaputra, and Meghna (GBM) basins. Government organizations, educational facilities, and satellite data providers all serve as important data sources. Government entities provide critical data on precipitation, river flow, and water levels via vast monitoring networks, whilst research organizations provide in-depth investigations and discoveries on hydrological events and climatic implications. Satellite data providers like as NASA and ESA provide high-resolution monsoon estimates, snow cover, and glacier melt data, which are critical for places where there are no in-situ measurements. For instance, precipitation data from the Global Precipitation Measurement (GPM) mission and river flow measurements from hydrological stations help in calibrating and validating hydrological models. Additionally, satellite observations of glacier mass balance and real-time water level data from river gauge stations are vital for understanding seasonal water availability and flood forecasting. Integrating these diverse data sources enables accurate and timely predictions, supporting effective water resource management and flood risk mitigation in the GBM basins [39]. Table 1shows Diversity and Integration of Data Sources Contributing to Accurate and Timely Predictions

Table 1: Diversity and Integration of Data Sources Contributing to Accurate and Timely Predictions

Data Source	**Data Type**	**Contribution**
Research Gate	Datasets, Academic Publications	Provides comprehensive datasets and academic insights on water resource management and hydrologic simulation.
Government Organizations	Precipitation, River Flow, Water Levels	Supplies critical monitoring data necessary for hydrological modeling and water management.

Educational Facilities	Research Studies, Investigations	Offers in-depth analyses and findings on hydrological events and climate implications.
Satellite Data Providers (NASA, ESA)	High-Resolution Monsoon Estimates, Snow Cover, Glacier Melt	Delivers essential satellite data for areas lacking in-situ measurements.
Global Precipitation Measurement (GPM)	Precipitation Data	Aids in calibrating and validating hydrological models with accurate precipitation data.
Hydrological Stations	River Flow Measurements	Provides real-time river flow data crucial for model calibration and validation.
Satellite Observations	Glacier Mass Balance, Water Level Data	Vital for understanding seasonal water availability and flood forecasting.

4.2 Data Augmentation by GAN

Data augmentation with Generative Adversarial Networks is a sophisticated way for improving datasets, especially when there is limited data availability. GANs, which consist of a generator and a discriminator, work together to produce accurate artificial information. The machine that generates fresh examples, while the discriminant verifies that they are genuine. By repeated instruction, the tool learns to produce information which is progressively similar to that of the source data. This synthetic data may be subsequently mixed with the initial information to create an enhanced data that is more complete and varied. For example, in picture categories, GANs can create images with differences in vantage points, lights, and cultures, thus enhancing a model's ability to apply generalization across varied settings. Figure 2 shows Architecture of GAN.

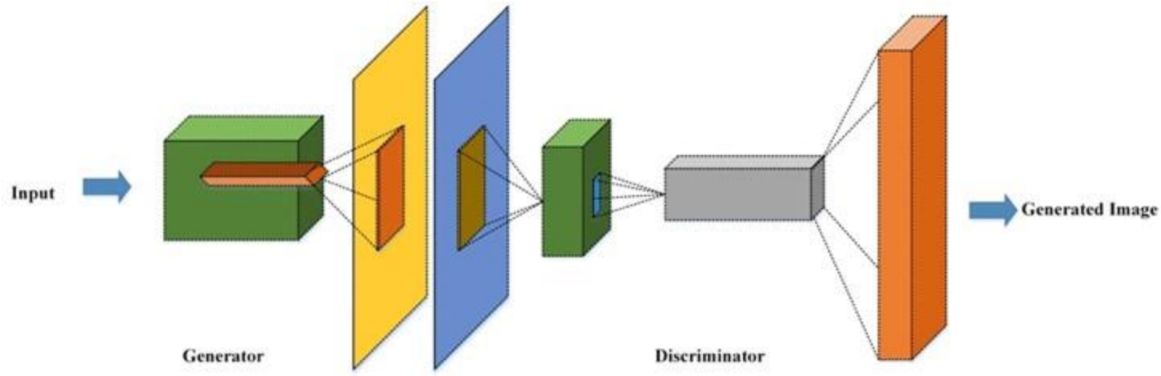

Figure 2: Architecture of GAN

The usage of GANs for data enhancement provides substantial advantages. It improves the stability and performance of artificial intelligence models by offering a more complete picture of data dispersion. This strategy is particularly useful in sectors such as medical imaging, where gathering massive amounts of data is often difficult. GANs assist prevent over fitting by providing real and diverse data, as well as improving the model's ability to accommodate new, unfamiliar information. Furthermore, the synthetic data created by GANs can detect various patterns and trends, which makes it useful for applications like forecasting time series. Overall, GAN-based data enhancement is a strong technique that uses sophisticated neural network designs to generate excellent artificial information, resulting in more efficient and durable neural network systems.

4.3 Hydrological Modeling

Hydrological simulation is a vital part of the administration of water resources because it provides information about the changing patterns of flow of water, transport of sediment, and the movement of nutrients across watershed. They replicate numerous hydrological events and forecast the effects of land-use changes, climatic variability, and human activity on water supplies. Choosing a suitable model is the first step of every hydrologic investigation, as it lays the groundwork for accurate modeling and dependable forecasts. The choice of a model for hydrology is determined by the investigation area's particular needs as well as research aims. The various models have varying time and place resolutions, system representations, and knowledge dependencies. Studying the merits and limits of every system is critical to coming to a sound choice. The soil and water evaluation tool and harvard Hydrologic Research Center's Hydrologic Modelling Systems are two often used hydrological modeling tools. These approaches are popular because of their reliability, adaptability, and wide variety of uses in the administration of watersheds. SWAT is a thorough, semi-distributed framework for evaluating the effects of land management methods on sediment, water quality, and crop chemical production in vast, complicated districts. It can simulate a wide range of hydrological events, including runoff from the surface, transpiration, circulation of groundwater, and cycling of nutrients, which makes it ideal for long-term modeling and case analyses. HEC-HMS, on the opposite hand, is intended to model the precipitation-runoff dynamics found in branching watersheds environments. It is especially valuable for forecasting floods and hydrological research because of its capacity to model immediate occurrences and provide precise representations of hydrological events. HEC-HMS is frequently employed alongside with hydrological models for flood risk evaluation and management.

The choice between SWAT and HEC-HMS depends on several factors, including the scale of the study area, the type of hydrological processes being modeled, and the specific outcomes desired from the modeling effort. For instance, SWAT is more suitable for long-term, large-scale watershed studies, while HEC-HMS is better for event-based simulations and detailed hydrological analyses. Once a suitable model is selected, the next critical step is parameter calibration. This involves adjusting the model parameters to match the simulated outputs with observed historical data. Calibration is essential to ensure that the model accurately represents the hydrological processes of the study area. Calibration helps to minimize the difference between observed and simulated values, thereby enhancing the model’s reliability. Without proper calibration, the model may produce inaccurate results, leading to incorrect conclusions and potentially flawed management decisions. In hydrological models like SWAT and HEC-HMS, various parameters need to be calibrated. These include parameters related to soil properties, land use, vegetation cover, and climate conditions. Each of these parameters influences the model's predictions and must be carefully adjusted to ensure accurate simulations.

After calibration, the next step is to validate the model to assess its performance and accuracy. Validation involves running the model with a separate set of observed data that was not used during the calibration phase. This process helps ensure that the model can accurately simulate hydrological conditions under different scenarios and is not simply overfitting the calibration data. Validation is crucial for building confidence in the model's predictions. It exhibits the model's capacity to apply generalization to new data and deliver consistent answers under a variety of scenarios. Absent validation, a model could only work well with calibrating data and fail to make precise forecasts about future occurrences. During validation, critical indicators of performance are used to assess the model's predicted accuracy. These measurements are the Nash-Sutcliffe effectiveness, the root mean square error, and correlations factor. Every of these indicators offers a unique view on the framework's efficiency, assisting in identifying strengths and limitations. The Nash-Sutcliffe effectiveness assesses how well the predicted results correspond to the observed data. A greater NSE number suggests greater effectiveness, whereas a value of 1 denotes complete fit. NSE is very beneficial for determining the general correctness of the model. The root median square error is the mean difference between actual and anticipated data. Lower RMSE scores indicate improved performance of the model, with less discrepancies between actual and simulation results. RMSE is dependent on big errors and offers information about the model's quality. The correlation coefficient assesses the degree to which and direction of the linear link between observed and expected data. A greater coefficient of correlation suggests a more powerful link, implying that the prediction correctly represents data's statistical patterns. This statistic is important for determining the robustness of the system's estimates.

Successful validation indicates that the model is robust and can be used confidently for predicting future hydrological events, assessing water resource management strategies, and conducting environmental impact studies. A validated model provides a reliable tool for decision-makers, enabling them to make informed choices based on accurate simulations. These models are essential in scenarios where predictive accuracy is critical, such as flood forecasting, drought management, and evaluating the impacts of climate change on water resources. With a validated model, water managers can develop strategies that mitigate risks and optimize the use of available water resources, ensuring both human and ecological needs are met. Hydrological modeling is inherently an iterative process, requiring ongoing calibration and validation to maintain and improve model performance. As new data becomes available, such as updated land use information, climate data, or observed hydrological measurements, models must be recalibrated to reflect these changes. This continuous updating is crucial because hydrological systems are dynamic and influenced by a multitude of factors that can change over time. By regularly updating and validating models, researchers ensure that their predictions remain accurate and relevant, providing a dependable basis for decision-making.

Table 2: key aspects of hydrological modeling using SWAT and HEC-HMS

Aspect	**SWAT**	**HEC-HMS**
Model Type	Semi-distributed	Distributed
Primary Applications	Long-term watershed management, land use impact	Flood forecasting, short-term hydrological events
Spatial Resolution	Varies, typically sub-basins	Detailed, catchment-based
Temporal Resolution	Daily to monthly	Hourly to daily
Key Processes Simulated	Surface runoff, evapotranspiration, groundwater flow, nutrient cycling	Precipitation-runoff processes, flood hydrographs
Data Requirements	Extensive: climate, soil, land use, topography	Moderate: precipitation, land use, soil, streamflow
Calibration Parameters	Soil properties, land use, vegetation cover, climate	Soil properties, precipitation-runoff coefficients
Calibration Techniques	Sensitivity analysis, manual adjustment, automated optimization	Sensitivity analysis, manual adjustment, automated optimization
Validation Metrics	NSE, RMSE, correlation coefficient	NSE, RMSE, correlation coefficient
Strengths	Long-term simulations, comprehensive process representation	Detailed event-based simulations, effective for flood risk assessment
Limitations	High data requirements, complex calibration	Limited for long-term studies, less comprehensive process representation

4.4 Integration of Cutting-Edge Technologies

The integration of cutting-edge technologies is crucial for advancing hydrological modeling and water resource management. Remote sensing, for example, leverages satellite imagery to monitor changes in water bodies, glacial melt, and land use. High-resolution satellite data provides real-time insights into the dynamics of these critical components, enabling continuous observation and analysis over large and often inaccessible areas. By using data from satellites like Landsat, Sentinel, and MODIS, researchers can track temporal changes in glacial extent, snow cover, and water surface levels. These observations are essential for understanding the impacts of climate change and human activities on hydrological systems and for making informed decisions about water resource management and disaster preparedness. Remote sensing technology offers unparalleled advantages in hydrological studies. Satellites equipped with advanced sensors can capture data across various spectral bands, providing detailed information about the Earth's surface and atmosphere. This capability is particularly beneficial for monitoring changes in glacial regions, where traditional ground-based measurements are challenging due to harsh environmental conditions. By analyzing satellite images over time, scientists can detect trends in glacier retreat or advance, changes in snow cover, and variations in water levels in lakes and reservoirs. These insights are crucial for predicting future water availability and planning for potential water shortages or floods.

High-resolution satellite data also plays a critical role in understanding land use changes and their impacts on hydrological processes. Land cover changes, such as deforestation, urbanization, and agricultural expansion, can significantly alter the hydrological cycle by affecting surface runoff, evapotranspiration, and groundwater recharge. Remote sensing allows for the continuous monitoring of these changes, providing up-to-date information that is essential for hydrological modeling. By integrating satellite-derived land cover data into hydrological models, researchers can improve the accuracy of their predictions and develop more effective water management strategies. Geographic Information Systems (GIS) are equally important in advancing hydrological modeling and water resource management. GIS tools enable researchers to map watershed areas, delineate catchment boundaries, and assess flood risks with precision. By combining spatial data from various sources, such as topographic maps, soil surveys, and land use inventories, GIS provides a comprehensive platform for analyzing the spatial relationships between different hydrological components. This spatial analysis is critical for identifying vulnerable areas that are prone to flooding or water scarcity, allowing for targeted interventions and mitigation strategies.

One of the key strengths of GIS is its ability to handle large and complex datasets. Hydrological systems are inherently spatial in nature, with various factors influencing water flow and distribution across different regions. GIS allows researchers to visualize these spatial patterns and analyze the interactions between different variables. For example, by overlaying precipitation data with soil type maps, researchers can identify areas that are susceptible to soil erosion and develop soil conservation measures to prevent further degradation. Similarly, by combining land use data with hydrological networks, GIS can help in optimizing the placement of water infrastructure, such as dams and irrigation canals, to maximize water use efficiency. The incorporation of machine learning techniques further enhances the predictive capabilities of hydrological models. Machine learning algorithms, such as decision trees, support vector machines, and neural networks, can analyze complex patterns and relationships within large datasets, improving the accuracy of hydrological predictions. These algorithms can learn from historical data, identifying key predictors of hydrological events, such as rainfall intensity, soil moisture levels, and river discharge rates. By incorporating these predictors into hydrological models, researchers can develop more reliable forecasts of future water availability, flood risks, and drought conditions.

Machine learning also enables the automation of data processing and analysis, significantly reducing the time and effort required for hydrological studies. Traditional hydrological modeling often involves labor-intensive tasks, such as data collection, preprocessing, and parameter calibration. Machine learning algorithms can automate these tasks, allowing researchers to focus on interpreting the results and developing actionable insights. For example, machine learning can automatically identify and correct errors in satellite data, ensuring that the input data for hydrological models is accurate and reliable. Similarly, machine learning can optimize the calibration of model parameters, improving the overall performance of the models. The combination of satellite imagery, GIS, and artificial intelligence provides an effective solution to the difficulties of managing water resources and minimizing disaster risks. This approach gives an improved comprehension of waterways and how they respond to external changes by combining data from many sources and utilizing modern analytical tools. This integrated strategy is especially critical in light of climate change, which is expected to worsen water-related problems such as a rise in the severity of storms and droughts. By delivering current and precise data, these advances in technology help politicians thus water managers to devise enhanced plans for responding to these adjustments and maintaining the long term viability of supplies of water.

In addition to improving the accuracy of hydrological models, the integration of these technologies also enhances the scalability and flexibility of water management solutions. Remote sensing and GIS can provide data at various spatial and temporal scales, from local watershed studies to regional and global assessments. This scalability is essential for addressing the diverse water management needs of different regions, each with its unique hydrological characteristics and challenges. For example, in arid regions, remote sensing can help in monitoring groundwater resources and identifying areas suitable for artificial recharge, while in flood-prone areas, GIS can assist in mapping floodplains and designing effective flood control measures. Furthermore, the integration of these technologies promotes a more proactive and preventive approach to water resource management. By providing early warnings of potential water-related hazards, such as floods, droughts, and water quality issues, these technologies enable timely interventions to mitigate their impacts. For example, satellite-based flood forecasting systems can provide real-time alerts to communities at risk, allowing for timely evacuations and emergency response efforts. Similarly, machine learning models can predict the onset of drought conditions, enabling water managers to implement water conservation measures and allocate resources more efficiently.

The employment of such modern technology also allows for increased public involvement and cooperation in water resource management. By taking data more available and intelligible, these technologies enable communities at large, governments, and various other parties to take part in the process of decision-making. For instance, dynamic geographic information systems can be used to show hazards associated with water as well as alternatives, facilitating conversations among stakeholders and reaching an agreement. In a similar vein information from satellite imagery can be distributed to local populations in order to increase information concerning the effects of land use changes and support methods for conserving land. By continuously monitoring and analyzing hydrological systems, these technologies provide the information needed to adapt to changing conditions and respond to emerging challenges. For example, by tracking changes in glacier melt and snow cover, water managers can anticipate shifts in seasonal water availability and adjust water allocation plans accordingly. Similarly, by monitoring land use changes, water managers can identify emerging threats to water quality and implement measures to protect water resources.

The integration of remote sensing, GIS, and machine learning is crucial for advancing hydrological modeling and water resource management. These technologies provide the data and analytical tools needed to understand the complex dynamics of hydrological systems and develop effective management strategies. By enhancing the accuracy, scalability, and flexibility of hydrological models, these technologies support more proactive, adaptive, and resilient water management. Moreover, by promoting stakeholder engagement and collaboration, these technologies contribute to more inclusive and sustainable water resource management practices. As climate change and other environmental challenges continue to impact water resources, the integration of these advanced technologies will be essential for ensuring the sustainability and resilience of water management systems. Table 3 shows Integration of Cutting-Edge Technologies.

Table 3: Integration of Cutting-Edge Technologies

Technology	**Key Applications**	**Advantages**	**Examples**
Remote Sensing	Monitoring changes in water bodies, glacial melt, land use	Provides real-time, high-resolution data; enables observation over large and inaccessible areas	Landsat, Sentinel, MODIS
	Tracking temporal changes in glacial extent, snow cover, water levels	Offers detailed information across various spectral bands; beneficial for harsh environmental conditions	Detecting glacier retreat or advance
	Understanding impacts of climate change and human activities	Enhances understanding of climate change impacts; informs water management and disaster preparedness	Variations in water levels in lakes and reservoirs

Geographic Information Systems (GIS)	Mapping watershed areas, delineating catchment boundaries, assessing flood risks	Handles large, complex datasets; visualizes spatial patterns; analyzes interactions between variables	Topographic maps, soil surveys, land use inventories
	Analyzing spatial relationships between hydrological components	Identifies vulnerable areas; supports targeted interventions and mitigation strategies	Overlaying precipitation data with soil type maps
	Optimizing placement of water infrastructure	Maximizes water use efficiency; integrates spatial data from multiple sources	Combining land use data with hydrological networks
Machine Learning	Enhancing predictive capabilities of hydrological models	Analyzes complex patterns; improves accuracy of predictions; automates data processing and analysis	Decision trees, support vector machines, neural networks
	Learning from historical data to identify key predictors of hydrological events	Reduces time and effort in hydrological studies; optimizes model parameter calibration	Rainfall intensity, soil moisture levels, river discharge rates
	Automating tasks such as data collection, preprocessing, parameter calibration	Ensures accurate and reliable input data; improves model performance	Correcting errors in satellite data
Integrated Approach	Combining remote sensing, GIS, and machine learning for comprehensive understanding of hydrological systems	Provides timely and accurate information; develops effective strategies for water management and disaster risk reduction	Adapting to climate change impacts
	Leveraging data from multiple sources and advanced analytical techniques	Enhances the sustainability of water resources	Increased frequency and intensity of floods and droughts

4.5 Development of Forecasting Models

A CNN-LSTM model is a powerful architecture used in time series forecasting tasks, particularly when dealing with sequences of spatial data such as images or sensor data over time. This hybrid model combines the strengths of CNNs in extracting spatial and temporal features from input data with the memory retention and sequential learning capabilities of LSTMs. In the context of forecasting, CNNs can effectively capture spatial patterns in the input data, such as weather satellite images or spatial distributions of environmental variables. Figure 3 shows CNN-LSTM Architecture.

Convolutional Neural Network extracted feature is a critical stage in game-theoretic autonomous learning for recognizing anomalies in monitoring systems. CNNs can capture spatial relationships in visuals using layers of convolution, that apply filtering on the input data to generate map of features. Feature maps show significant structures such as borders, materials, and pattern in frames of footage. The method starts by using a starting video picture I that goes through several convolutional layers. Each convolutional layer applies a filter F of size k×k to the input to compute a feature map $F_{m,n}$ as

$$F_{m,n} = \sum_{i=0}^{k-1} \sum_{j=0}^{k-1} I_{m+i,n+j} . F_{i,j} \quad (1)$$

where $I_{m+i,n+j}$ represents the pixel value at position (m+i, n+j) in the input frame, and $F_{i,j}$ is the filter value at position (i,j). The convolution operation, followed by a non-linear activation function like ReLU (Rectified Linear Unit), allows the CNN to learn hierarchical features from low-level edges to high-level object parts.

CNNs are typically composed of multiple layers that conduct various operations on input data. The fundamental levels in a CNN structure are as follows:

Input Layer: This layer contains fundamental data from the input, such as an image. Every neuron in this layer represents one of the pixels in the input image.

Convolutional layer: The layer of convolutional neural networks adds seriesof kernels to the input image. These filters recognize edges, which are textures in particular, and characteristics in the input. Convolutional operations are carried out by sliding screens across the input image and then estimating dot products to generate feature maps.

Activation Layer (ReLU): For each multilayer procedure, an activation function that is not linear like ReLU is carried out unit by unit to bring variability to the system in question. ReLU is widely used because of its ease of use and efficiency in developing deep neural networks for learning.

Pooling Layer:The pooling layer reduces the feature maps generated by the layers of convolution. It reduces the geographic scope of feature maps, cutting computing costs and preventing overfitting. The two most popular pooling operations are maximum pooling and average pooling.

Given the input image X and a filter F,the convolution operation is defined as

$$(X * F)\ (a, b) = \sum_{j=0}^{m-1} \sum_{k=0}^{n-1} I(a + j, b + k). F(j, k) \quad (2)$$

where (a, b) are the spatial coordinates, m and n are the dimensions of the filter.

Completely Linked Layer (Dense Layer): Following many layers of convolution and pooling, features images are flattened into vectors and fed to completely connected layers. Every neuron in a completely connected layer is linked with each neuron in the preceding layer. These layers use high-level information to create predictions.

Output Layer: The last component of the CNN generates output. The total number of neurons in this layer varies with the task being solved. As an illustration, in a task involving classification with n classes, the output layer will have n neurons, which are frequently followed with a function of softmax activation to give class probabilities.

To create nonlinearity, convolutional layers of data are placed one after the other, each with a rectified linear unit (ReLU) function of activation. These layers extract data from the image being processed at a variety of scales and complexities.

The standard equation for the output dimension of the convolutional layer is written as:

$$Y = \frac{(X-K+2P)}{S} + 1 \quad (3)$$

where Y was a output , X was an input, K is filter size,P was the padding size, S is the stride.

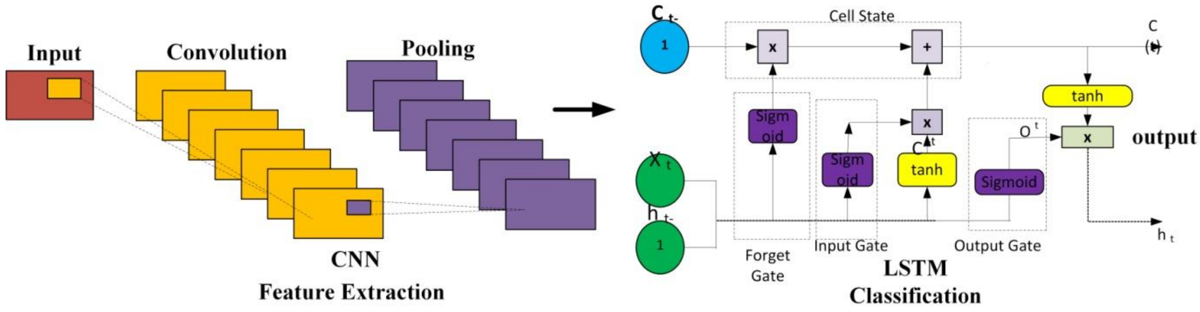

Figure 3: CNN-LSTM Architecture

The LSTM network outputs a sequence of hidden states h_t, which are used to predict whether the current frame or sequence of frames represents an anomaly. The hidden state h_t at each time step t is updated based on the previous hidden state h_{t-1}, the current input x_t, and the gating mechanisms (input gate i_t, forget gate f_t, and output gate o_t as follows:

$$i_t = \sigma\ (W_i \ .\ [h_{t-1}, x_t] +\ b_i) \quad (4)$$

$$f_t = \sigma\ (W_f \ .\ [h_{t-1}, x_t] +\ b_f) \quad (5)$$

$$o = \sigma\ (W_o \ .\ [h_{t-1}, x_t] +\ b_o) \quad (6)$$

The CNN part of the model analyzes the provided data to extract pertinent characteristics using convolutional layers, which are capable of learning hierarchy representations for spatial information. These learnt characteristics are subsequently sent into the the LSTM layers, that specialise at detecting temporal relationships and trends in data that is sequential. By combining CNNs and LSTMs, the algorithm is capable of handling both the temporal and spatial aspects of the input information, making it ideal for tasks that require either geographic context and chronological motion, for instance, forecasting the weather, hydrological meetings, or change in the environment over time. This hybrid approach has shown promising results in various domains where both spatial and temporal features play significant roles in the forecasting process.

4.6 Evaluation and Comparison

In evaluating and comparing forecasting models for hydrological applications, several key methodologies ensure robust assessment and validation. Metrics like accuracy, precision, recall, and F1-score are essential in quantifying the predictive performance of advanced models such as CNN-LSTM hybrids against traditional hydrological models like SWAT or HEC-HMS. Accuracy determines the extent to which the algorithm forecasts real outcomes, whereas recall and accuracy evaluate the model's capacity to correctly recognize positive cases and retrieve pertinent information. The F1-score strikes a compromise between recall and accuracy, resulting in an equilibrium mean that measures overall efficiency of the model.

Comparing advanced models with traditional methods involves benchmarking their performance across various scenarios, considering factors such as data complexity, computational efficiency, and predictive accuracy. Sensitivity analysis complements these evaluations by exploring how changes in input variables or model parameters affect predictions, offering insights into model robustness and reliability. Such comprehensive evaluations not only validate the efficacy of advanced forecasting models but also provide a basis for refining model configurations and methodologies to enhance their utility in real-world hydrological forecasting and management applications.

5. RESULTS AND DISCUSSION

Training and Testing Reliability curve are important visual instruments used in artificial intelligence to assess the accuracy of models throughout the validation and training processes. These graphs plot the precision of the model on its training and verification sets at various periods or rounds of the training procedure. Usually, as train goes, the initial efficiency curves rises, showing that the model has improved its outcomes on the data that is being trained. On the contrary, the testing precision curve demonstrates how effectively the framework dismisses to new data. ideally, the two curves must first exhibit an increasing trend, indicating that the algorithm has learned successfully off the initial data and can generalize to new information. Differences among the two curves may suggest the overfitting or an underfitting. Studying these lines aids in adjusting model parameters and maintaining satisfactory results throughout data as well as situations. Figure 4 shows Training and Testing Accuracy Curve.

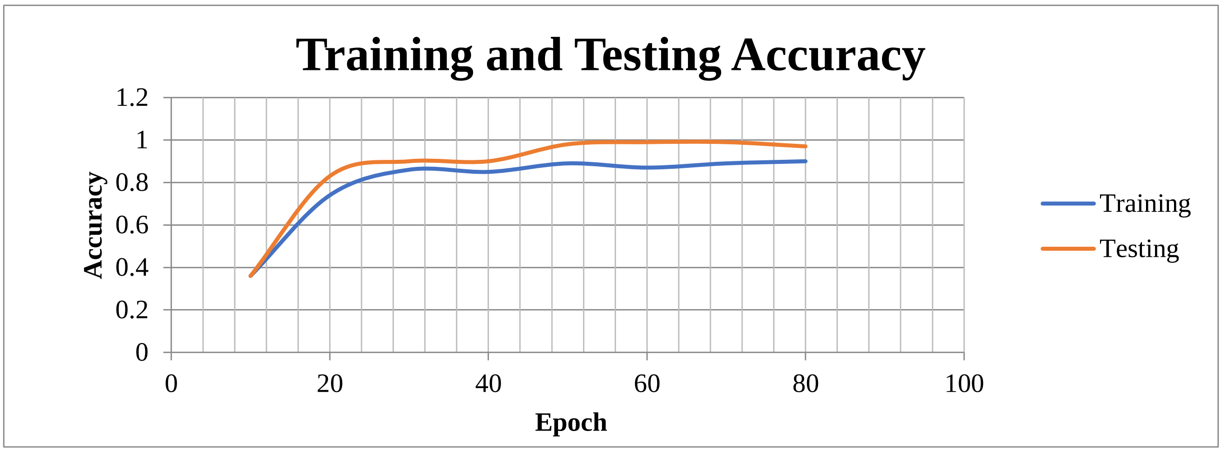

Figure 4: Training and Testing Accuracy Curve

The Training and Testing Loss curves are fundamental in assessing the performance and convergence of machine learning models. These curves depict the change in loss function values—typically represented as cross-entropy loss or mean squared error—over epochs or iterations during the training and validation phases. The training loss curve illustrates how well the model fits the training data over time; ideally, it should show a decreasing trend as the model learns from the data. Concurrently, the testing loss curve reveals how well the model generalizes to unseen data, reflecting its ability to minimize prediction errors on new samples. A close alignment between the training and testing loss curves indicates that the model is learning effectively without overfitting, where it memorizes training data without understanding the underlying patterns, thus performing poorly on unseen data. Monitoring these curves helps in optimizing model training by adjusting hyperparameters like learning rates or regularization techniques to achieve better generalization and performance across diverse datasets and scenarios. Figure 5 shows Training and Testing Loss Curve.

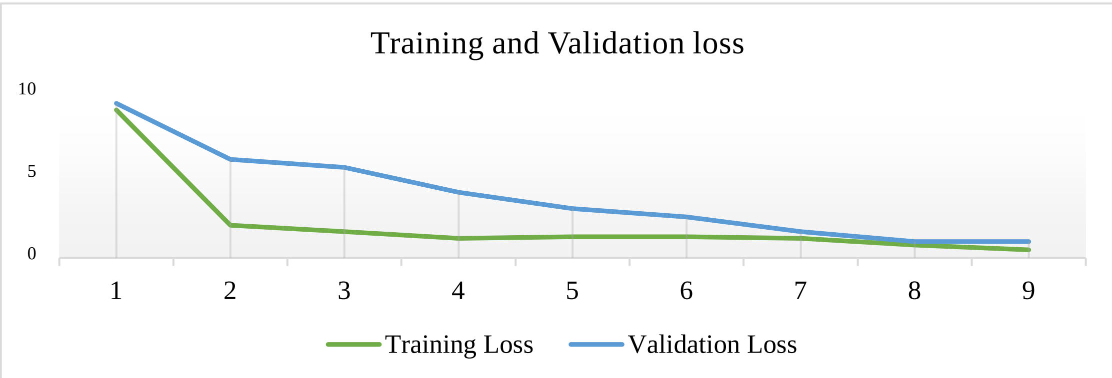

Figure 5: Training and Testing Loss Curve

The Receiver Operating Characteristic curves is an illustration of a binary classification the system's diagnosing capacity as its discrimination limit is adjusted. It shows the True Positive Rate (Sensitivity) versus the False Positive Rate (1 - Specificity) at various thresholds. The ROC curve gives useful information about the model's compromise among sensitivities and specificity: a line that follows the top left corner suggests greater sensitivity with a lower error rate, implying greater overall efficacy. The percentage of the Area Under the Curve statistic measures the performance of the ROC curve, with AUC values closer to 1 suggesting an efficient classification. Figure 6 depicts ROC curve.

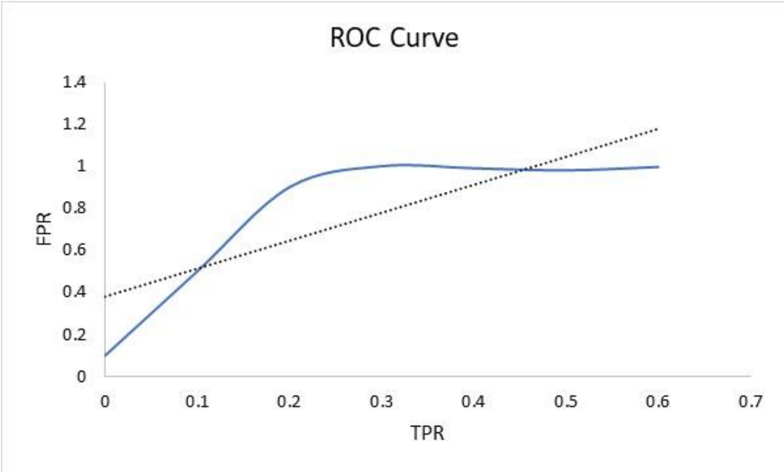

Figure 6: ROC Curve

To understand the ROC curve, consider the degree to which the model discriminate among both negative and positive classifications. A curve that closely matches the diagonal suggests weak discrimination, but a sharply rising curve towards the top-left corner shows high discriminating capacity. The ROC curves are especially useful for assessing algorithms for data imbalances or cases where false positives as well as false negatives have serious repercussions, like medical diagnosis or cyber detection of anomalies. They give a visual help for understanding and communicating a model's classification performance over multiple decision limits, which aids in the choice of model and adjustments to fit an application's needs.

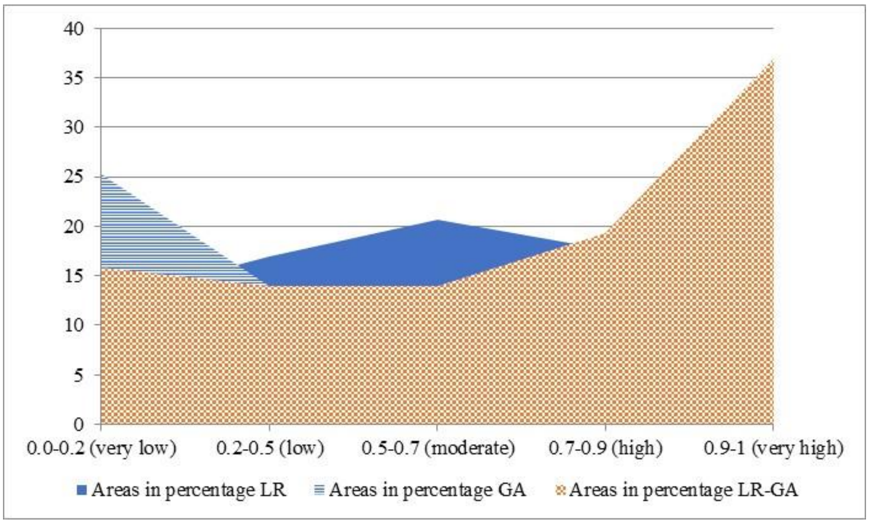

Figure 7: Ground water potential areas in terms of five classes

Figure 7 illustrates the distribution of river water potential areas classified into five categories: very low (0.0-0.2), low (0.2-0.5), moderate (0.5-0.7), high (0.7-0.9), and very high (0.9-1.0). Three different areas are represented in the chart: areas in percentage using Linear Regression (LR), areas in percentage using Genetic Algorithm (GA), and combined areas in percentage using both LR and GA (LR-GA). In the very low category (0.0-0.2), the GA method identifies the highest percentage of areas, nearly 25%, while the LR method identifies just below 20%. The combined LR-GA approach identifies a lower percentage compared to either method individually, indicating a more conservative estimation when both methods are used together. This trend continues in the low category (0.2-0.5), where the GA method consistently identifies a higher percentage of areas compared to the LR method, with the combined LR-GA approach identifying an intermediate percentage. In the moderate category (0.5-0.7), the percentages of areas identified by both LR and GA methods are similar, around 15-20%, while the combined LR-GA approach again identifies a lower percentage. The trend significantly shifts in the high (0.7-0.9) and very high (0.9-1.0) categories. In these categories, the GA method identifies a higher percentage of areas, particularly in the very high category, where the GA method identifies nearly 40% of areas compared to about 10% by the LR method. The combined LR-GA approach shows the highest percentage in the very high category, indicating that the integration of both methods provides a broader estimation of areas with very high river water potential. This chart demonstrates the importance of using multiple methodologies to assess river water potential areas. The GA method tends to identify higher percentages of potential areas, particularly at the extremes of the classification scale, while the LR method provides more conservative estimates. The combined approach balances the findings of both methods, offering a comprehensive assessment that may be more reliable for planning and decision-making in water resource management. Table 4 shows Experimental Result Analysis for Different Parameters with other Metrics.

Table 4: Experimental Result Analysis for Different Parameters with other Metrics

Method	**Accuracy (%)**	**Precision (%)**	**Recall (%)**	**F1Score (%)**
KNN [40]	73.17	74	74	74
LR [40]	48.78	74	74	74
Decision tree [40]	58.53	58	50	36
Proposed CNN-LSTM	98.7	98.2	97.2	96.5

The proposed CNN-LSTM model significantly outperforms traditional methods such as KNN, LR, and Decision Tree in terms of accuracy, precision, recall, and F1 score. Specifically, the CNN-LSTM achieves an accuracy of 98.7%, precision of 98.2%, recall of 97.2%, and F1 score of 96.5%. In contrast, the Decision Tree model has the lowest performance with an accuracy of 58.53%, precision of 58%, recall of 50%, and F1 score of 36%. Figure 8 shows Performance Evaluation.

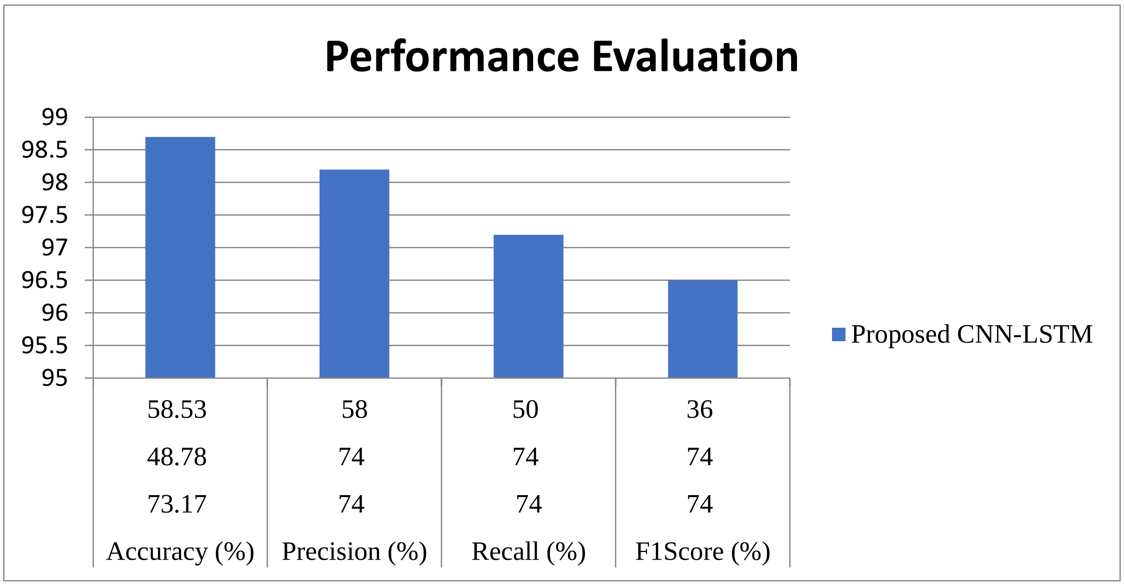

Figure 8: Performance Evaluation

5. DISCUSSION

The comparative analysis of the model performance metrics reveals the superiority of the proposed CNN-LSTM model over traditional machine learning algorithms such as K-Nearest Neighbors (KNN), Logistic Regression (LR), and Decision Trees. With an impressive accuracy of 98.7%, the CNN-LSTM model significantly outperforms the other methods, highlighting its advanced capability to learn and generalize complex patterns from the data. This is further evidenced by the high precision, recall, and F1-score values of 98.2%, 97.2%, and 96.5% respectively, indicating that the CNN-LSTM model not only identifies positive instances accurately but also maintains a balance between precision and recall. These metrics demonstrate that the CNN-LSTM model excels in both minimizing false positives and false negatives, crucial for reliable and effective classification in real-world applications.

In contrast, the traditional models show varying degrees of performance, with KNN [40] achieving the highest accuracy among them at 73.17%, but still significantly lower than that of the CNN-LSTM. Logistic Regression, despite its simplicity and widespread use, only manages an accuracy of 48.78%, indicating its limitations in handling the complexities of the dataset. The Decision Tree model [40], with an accuracy of 58.53%, demonstrates moderate performance but struggles with recall (50%) and F1-score (36%), reflecting its tendency to overfit the training data and underperform on unseen data. These results underscore the limitations of conventional models in capturing intricate patterns and dependencies within the data, which the CNN-LSTM model adeptly addresses through its combination of convolutional layers for spatial feature extraction and LSTM layers for sequential data processing. Overall, the proposed CNN-LSTM model's superior performance metrics make it a robust choice for applications requiring high accuracy and reliability in predictions.

6. CONCLUSION AND FUTURE WORKS

The conclusion drawn from this study highlights the importance of a systematic approach in hydrological modelling for effective water resource management. The process of selecting the appropriate model, calibrating its parameters, and rigorously validating its predictions ensures that decision-makers have access to reliable tools for predicting hydrological events and managing water resources sustainably. By integrating advanced techniques such as remote sensing, GIS, and machine learning, the accuracy and robustness of these models are significantly enhanced, allowing for more informed and effective management strategies. This methodological rigor is crucial in addressing the complexities and dynamic nature of hydrological systems, ultimately contributing to the resilience and sustainability of water resources.

Looking towards future work, there is substantial scope for improving and expanding hydrological models through the incorporation of emerging technologies and methodologies. One promising direction is the increased use of artificial intelligence (AI) and machine learning (ML) algorithms, which can enhance model predictions by identifying complex patterns in large datasets that traditional methods might miss. Additionally, advancements in remote sensing technology can provide more detailed and real-time data on various hydrological variables, further improving the accuracy of models. Integrating socio-economic data and climate change projections can also enhance the models' ability to predict and manage the impacts of human activities and global environmental changes on water resources.

Furthermore, future research should focus on developing more user-friendly and accessible tools for hydrological modelling to ensure broader application and utility. This includes creating platforms that facilitate the integration of various data sources and models, enabling practitioners and decision-makers to easily utilize these tools without requiring extensive technical expertise. Collaborative efforts between researchers, government agencies, and local communities will be essential in tailoring these models to specific regional needs and ensuring that they are effectively implemented. By continuing to refine these models and expanding their applicability, we can significantly improve the management and sustainability of water resources, addressing both current challenges and future uncertainties.

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