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AI-Driven Solutions For Achieving SDG's: Harnessing Machine Learning To Address Global Sustainability Challenges

Pooja H[1], K S Rajeshwari[2], Dr. Shweta S. Kaddi[3], ANSHUN CAI[4], Vijayanand Selvaraj[5], Dr. T.Thirumalai kumari[6]
[1]Associate Professor, Department of Computer Science and Engineering,JSS Academy of Technical Education, Bengaluru 560060, poojah@jssateb.ac.in
[2]Associate Professor, Department of Computer Science and Engineering,JSS Academy of Technical Education, Bengaluru 560060, Karnataka, ksrajeshwari@jssateb.ac.in
[3]Assistant Professor, Department of Computer Science and Engineering,JSS Academy of Technical Education, Bengaluru 560060, Karnataka, swethaskaddi@jssateb.ac.in
[4]Faculty of Education , Shinawatra University, caianshun102132@163.com, 0009-0007-0438-4063
[5]AI & Data Strategist , Information Technology Professional, Houston, Texas, USA.
[6]Assistant professor, Department of Computer Application , School of Computing Sciences, Vels Institute of Science, Technology & Advanced Studies (VISTAS). Chennai- 600117, umakumari2103@gmail.com, 0009-0007-6902-3330

Abstract– *The Sustainable Development Goals (SDGs) established by the United Nations offer a global guide to building peace, prosperity, and sustainability of the environment. Nevertheless, surveillance and reaching these objectives are a complex process with limited data, material availability, and overall inefficiency of the system. Artificial Intelligence (AI), notably Machine Learning (ML), can be presented as such a potent instrument that can help close such gaps, as advanced analytics, prediction models, and data-driven decision-making. This essay examines the use of AI-based solutions of which ML applications are the most widespread ones, how they are being utilized in different spheres to speed up the process of SDGs achievement. It researches the existing approaches, the studies connected with them, the practical applications, and the outcomes already recorded. Limitations, ethical implication, and future directions within the context of embedding AI into sustainability models are also the assessments within the study. The results indicate that although ML has a huge potential in improving sustainability monitoring, it needs to be implemented strategically and be governed in a way to make its operations inclusive and equitable to all.*
Keywords– *Artificial Intelligence, Machine Learning, Sustainable Development Goals, SDGs, Sustainability, Global Challenges, Predictive Analytics, Climate Action, AI Ethics, Data-Driven Policy*.

I. INTRODUCTION

Demands to tackle issues facing the world like poverty, climate change, inequality, and scarcity of resources are as high as ever. To address these increasing issues, the 2030 Agenda of Sustainable Development was endorsed by the United Nations in 2015 that gives 17 Sustainable Development Goals (SDGs). The goals are a universal guideline that aims at compelling the nations to place their development projects in line with the world agenda that has to do with social, economic and environmental sustainability. The objectives themselves are very ambitious and broad in nature but getting there is very complex. Whether it is the data collection and performance tracking, effective resource allocation, and policy implementation, SDG development requires a scalable and innovative solution that is sensitive to the context of issues [14].In the recent years, Artificial Intelligence (AI) came to appear as a strong technological model that would be able to radically shift the perspectives with which the global sustainability can be addressed. Machine Learning (ML) is one of the AI fields that has drawn special interest because it requires no systematic programming to make predictions or decisions or recognizes the patterns on the basis of the data presented. The use of ML is growing across spheres, including healthcare, agriculture, urban planning, and environmental protection, thus providing essential assistance in tracking, controlling, and speeding up the interventions related to SDG. As an example, governments can use ML-based models to predict agricultural output to prevent hunger, to track infectious disease outbreaks, minimize the traffic load to achieve a low output of emissions, or the areas at risk of the fall of climate disasters [8].The key capacity of ML lies in the possibility to process and analyze big amounts of heterogeneous data. Post-sustainable development, the amount of data that is relevant to the sustainable development is more than ever. Nonetheless, it is impractical to investigate such large and multidimensional volumes of data manually, neither in terms of scalability nor time. ML has an automatic, adaptive methodology that will help obtain action clues in the form of data streams in real-time. As an example, satellite images using ML algorithms can be used to monitor deforestation and other elements of biodiversity with a large degree of precision, and Natural Language Processing (NLP) models can be used to analyze the discourse of the population and estimate the attitude to sustainability policy. Although promising, the implementation of ML within the framework of SDGs is at an early developmental stage that is associated with great challenges [7]. Aberrant data availability and quality is one large challenge, particularly verging into low- and middle-income nations with fewer resources and internet know-how. ML models work best well-labeled and large data. In most developing environments, this kind of datasets is either too sparse, old, or prejudiced, so it bounds the reliability and fairness of AI-based intervention. In addition, transparency of the algorithm, data security and ethical control lead to the problem of unseen effects and the possibility of strengthening social inequality. The other complexity has been the interdisciplinary character of sustainability issues. Effective implementation of ML needs more than just technical knowledge; other knowledge areas like public health, environmental science, policy and education, are also essential [9]. An effective AI-based solution thus needs to be able to bind the advancement of technology and human-based design to ensure systems are situation-adaptable and cultural-sensitive. Also, the majority of the already offered AI solutions have been worked out and applied by a small number of technologically iconic states and companies that beg the question of equal access, sovereignty over information and international cooperation.Furthermore, SDGs implementation requires governments, businesses, non-governmental organizations, and grassroot groups to work together. Artificial intelligence projects need to be in tandem with the strategy and the governing body to guarantee that the technological improvements that are achieved can be converted into a practical effect on the ground. Yet, there tends to be a gap between ML developers and policy makers, and, hence, there is no integration of algorithmic insights into decision making. To bridge this divide, it has to put in place platforms and build partnerships that enable co-creation, knowledge sharing, and trust among them [10].However, the possibilities of AI, especially its ML component, as the concept of a sustainability force multiplier are undeniable. Such applications of ML as climate modeling have led to a very sharp increase in accuracy of forecasts, allowing more proactive and intelligent management of a disaster. The predictive models will help in the optimization of the vaccination campaigns, epidemics forecasting, and the individualization of medical treatment in the field of public health. Within the field of energy, AI is being utilized to rationalize smart grids as well as enhance energy consumption, which has a direct influence on Goal 7 (Affordable and Clean Energy) of the SDGs. Equivalent innovations can be viewed in the areas of water resource guidance, education access programs, employment matching algorithms and financial investment frameworks [12-13].With nations being unable to fulfill the SDG obligations and adding to the challenge the world-wide crises (like COVID-19 pandemic) and geopolitical strains, data-driven tools leverage is no more a matter of efficiency, but a question of necessity. The inclusion of ML into the SDG ecosystem is a rare chance to speed up the developments, yet with the responsible, non-discriminating, and inclusive application method. What is necessary is to go beyond technological euphoria and rather take up a critical and impact-oriented perspective where both its power and risk is considered in an ML-driven system.The paper shall discuss how machine learning is being implemented in different fields to help in supplementing and boosting accomplishment of SDGs. It reads on existing applications, emerging trends, frameworks of methods and the real life case studies. Moreover, the paper covers limitations and challenges of using ML in sustainability aspects and suggests recommendations on possible improvements of the positive outcome of its adoption. Incorporating academic, industrial, and policy device perspectives, this project seeks to offer an all-inclusive view on the role that AI can sustainably and equitably enable in the future [15].Novelty and Contribution The work has a few distinctive contributions to the emerging discipline of AI and sustainable development. In contrast to the literature that was focused on a certain isolated field (e.g., healthcare, agriculture or climate modeling), the paper follows a wide, cross-sectoral approach that aligns Machine Learning applications with the SDGs on a system-wide level. This way, it approaches the interdependence of the issues related to sustainability and demonstrates how using ML would allow looking at shared data infrastructure and interdisciplinary methods to achieve overlapping objectives [6].The first innovation of the present study is that it aims at reconciling ML practices and the UN SDG agenda targets and indicators. Instead of abstract theoretical accounts on the abilities offered by the AI, the paper bases its analysis on the measurable results and performance indicators adopted by the governments and international organizations. This alignment contributes to the fact that the results may be more practical, and policymakers can incorporate ML knowledge into official monitoring and evaluation structures.The second contribution would be the idea of the assessment of ML applications on the terms of technical readiness in combination with socio-ethical reasoning. The research looks at AI as not a silver bullet but rather analyzes the dangers of possible biasness, inequality, and opacity of ML systems. It focuses on such requirements as the inclusive design, participatory governance, and human-in-the-loop models that guarantee human-friendly AI-based tools that will not increase disparities among the world populations.Also, the paper proposes a new taxonomy of categorizing ML-based SDG solutions into four categories based on the data availability, model complexity and scalability, and policy integration. The framework could assist practitioners as well as researchers to evaluate the sustainability and viability of intended AI interventions. It also finds out the areas which are under-researched like SDG 10 (Reduced Inequalities) and SDG 16 (Peace, Justice and Strong Institutions) where ML might be more involved with the targeted innovation [5].Lastly, the paper offers practical implications, including the use of real-life case studies and obstacles of implementation as a source of analysis. It provides strategic advice to governments, non-governmental organizations and developers on how to co-develop AI solutions, create open data communities, and develop structural capacity in institutions to sustainably employ AI. This is an integrated and practical procedure that dictates the significance of this paper in bringing to the forefront of the discussion of AI for good, and a useful source of information to the stakeholders operating in the field of cross-referencing technology and worldwide development.

II. RELATED WORKS

In 2025 P. Zakaria et.al., [16] suggested the AI, and specifically, Machine Learning, and sustainable development have fast become a potentially fruitful interdisciplinary field. Researchers have reported during the last 10-year period on the enjoyment of the benefits of ML in the facilitation and improvement of the realisation of the Sustainable Development Goals (SDGs) through offering analytical power over big, multi-faceted data and streamlining decision-making. Through such investigations, it has been realised that ML can solve various global sustainability challenges such as climate change, food security, access to healthcare, access to education, and urban infrastructure.A significant motif that is presented by existing studies consists of ML application in environmental surveillance and climate action. The satellite imagery, weather data, geographical data, and other satellites-derived information are used in ML algorithms to analyse land fires, wild fires, and to predict them, air and water quality as well as modelling climate change scenarios. The applications align directly with SDG 13 (Climate Action), SDG 14 (Life Below Water) and SDG 15 (Life on Land). Through the presentation of precise, real-time data about environmental patterns, ML improves the capability of a policymaker and an organization to construct specific interventions and quantify the results of their sustainability initiatives.ML has provided enormous potential in aiding SDG 2 (Zero Hunger) in the agriculture sector. The crops to be harvested are predicted using predictive model, diagnosing (predicting) the plant diseases, determining the quality of soil, and optimizing irrigation systems. Precision agriculture with ML helps farmers make sound decisions by analyze information recovered by aviation vehicles, sensors, and weather trends of the past. These research findings emphasise that the implementation of ML in agriculture can make it more productive and less wasteful and provide food security even in the most limited areas.In 2025 M. Ibrahim et al., [11] proposed the Medical care is yet another sector where ML is gradually finding a way to aid the SDG 3 (Good Health and Well-being). Research has been carried out on how early ML models can be used to recognize a disease, engage in medical image analysis, recommend personalized treatment plans, and forecast epidemics. They are used to analyze huge amounts of medical information including electronic health records, laboratory tests outcomes, genome sequences among others and can help in making more accurate diagnoses, and more effective treatments. Particularly, ML based health surveillance systems have played crucial roles in preparing against health pandemics since they are able to identify the outbreak and react to it in real time by analyzing data.Urban planning and smart cities were widely researched along with SDG 11 (Sustainable Cities and Communities) in terms of ML integration. ML is utilized to fine-tune the traffic, regulate the energy usage, spot weak links in the infrastructure, and predict the trend of the urban development. These applications not only enhance the quality of the life in the city, but also they help to reduce carbon emissions and increase the resilience of the city infrastructure. Moreover, scientific literature has shown the effectiveness of integrating ML technologies with Internet of Things (IoT) technologies to make cities resilient systems, which can change according to the conditions of the time.There is a flourishing number of studies devoted to ML application in facilitating access to quality education, which coincides with SDG 4 (Quality Education). ML algorithms are used to create such systems as intelligent tutoring systems, personalized learning platforms, and automated assessment. These are individual-oriented systems that respond to the needs of students and offer a real-time feedback, enhancing the educational results. There is a tendency to support inclusiveness in the studies of this field by focusing on underserved groups and designing the tools that could be used in low-resource settings.Another rising development that is seeing its use in ML is financial inclusion in line with SDG 1 (No Poverty) and SDG 8 (Decent Work and Economic Growth). It has been shown how ML can help create credit scores systems for people lacking a formal financial history so that individuals can have access to microloans and insurance. ML is also improving the detection of frauds, separation of customers and studying of market trends to create more effective and inclusive financial systems.When speaking of clean energy, studies have explored the application of ML in the process of energy demand forecasting, optimization of integrating renewable energies into a power system, and energy storage management. Those studies contribute to SDG 7 (Affordable and Clean Energy) as they can show how ML can be used to increase independence of fossil fuels, and make energy systems more efficient. Another area where predictive maintenance is of importance is energy centres, like solar panels and windmills.In 2024 M. Al-Raeei et.al., [2] introduced the number of the studies on the use of ML in the sphere of water management also represents a substantial number and often leads directly to the SDG 6 (Clean Water and Sanitation). The detection of leakages in pipelines, the prediction of water demand, the monitoring of ground water quality and modelling of flood risks are being done using ML models. The solutions will help municipalities and utilities to guarantee equity and sustainability of access to water resources. Most research on sustainability goals is often on individual goals although there has been an increased appreciation of how the sustainability goals are interdependent. There are growing investigations on how to design ML models to engage several SDGs at the same time. As an example, an early warning system on drought based on ML could lead to multiple contributions to hunger targets, poverty targets, water availability targets, and climate action targets. System thinking and integrated modeling are emerging in the literature and are being used to encourage a more integrative notion of AI's role in sustainable development.Although being promising, a number of studies concern the pitfalls and risks of ML adoption in the context of sustainability. These involve the absence of representative datasets of a high-quality in most areas across the globe, especially in low-income developing areas. ML models can induce biased or inaccurate results, which would support the established disparities, without proper data. Moreover, studies have indicated the necessity to implement ethical AI usage, transparent decision-making with algorithms, personal privacy, and data sovereignty.What also comes out in the related literature is the dead zone between the development of AI and policies. Although ML models may give informative insights, their usefulness will be determined by the fact whether or not they will be well incorporated in the decision-making procedures and institutionalized in the society. The research indicates that ML will only be successfully used to achieve SDGs with cross-sector collaboration of different stakeholders, such as governments, innovators of the private sector, non-profits, and local communities. This not only requires formulation of governance systems, norms, and capacity building, but also the idea of sustainable AI ecosystems [4].Lastly, it has researched the prowess of inclusivity and equity towards ML tools to create sustainable development. The ML systems have to be created with the requirements of minority groups in mind so that the positive impact of AI on them was evenly distributed. This involves integrating the local expertise, making the language accessible, and coming up with culturally valuable and economic friendly solutions.Literature on ML in terms of its uses regarding SDGs is multidisciplinary and wide-ranged with ever-growing dimensions. It shows the potential impact of ML in terms of transforming global sustainability goals clearly and the importance of envisioning responsible, inclusive, and ethical approaches. As this branch of science is expanding, it ensures the continuity of innovation, advancing concepts and regulation so that the might of AI can serve the globe and its inhabitants.

III. PROPOSED METHODOLOGY

To operationalize AI-driven solutions toward SDG achievement, a multi-stage machine learning framework is adopted, focusing on data preprocessing, feature extraction, model training, prediction, and deployment [3]. The methodology integrates multiple datasets across domains-such as environmental, healthcare, agricultural, and financial indicators—and applies ML models tuned for different SDG tasks.

Data Aggregation and Preprocessing

Let the input dataset be defined as:

$$D = \{(x_i, y_i) \mid i = 1,2, \ldots, n\}$$

where x_i represents the input features (e.g., satellite data, survey metrics), and y_i is the corresponding target output (e.g., hunger index, CO_2 level).

Each feature vector is normalized to ensure consistent scale using min-max normalization:

$$x_i' = \frac{x_i - \min(x)}{\max(x) - \min(x)}$$

Missing values are handled using mean imputation:

$$x_j^{\text{filled}} = \frac{1}{n}\sum_{i=1}^{n} x_{ij}$$

Feature Engineering

Features relevant to each SDG category are extracted using Principal Component Analysis (PCA):

$$Z = XW$$

where Z is the matrix of principal components, X is the original feature matrix, and W contains the eigenvectors of the covariance matrix of X.

The variance explained by the selected components is evaluated as:

$$\text{Explained Variance } = \frac{\lambda_k}{\sum_{j=1}^{m} \lambda_j}$$

where λ_k is the eigenvalue of the k^{th} principal component.

Model Architecture and Training

Various ML models are explored, including Random Forest, Gradient Boosting, and Deep Neural Networks. For classification tasks (e.g., poverty level categorization), cross-entropy loss is minimized:

$$\mathcal{L} = -\sum_{i=1}^{n} y_i \log(\hat{y}_i)$$

For regression-based tasks (e.g., predicting CO_2 emissions or yield loss), mean squared error (MSE) is used:

$$\text{MSE} = \frac{1}{n}\sum_{i=1}^{n} (y_i - \hat{y}_i)^2$$

Models are optimized using stochastic gradient descent (SGD):

$$\theta := \theta - \eta \cdot \nabla_\theta \mathcal{L}(\theta)$$

where θ is the parameter vector, η is the learning rate, and $\nabla_\theta \mathcal{L}$ is the gradient of the loss function with respect to parameters.

Cross-Validation and Evaluation

To ensure generalization and avoid overfitting, K-fold cross-validation is used. For a given fold k:

$$\text{Validation Accuracy}_k = \frac{TP + TN}{TP + FP + FN + TN}$$

where $TP =$ true positives, $TN =$ true negatives, $FP =$ false positives, $FN =$ false negatives. Additionally, R^2 score is used for regression-based indicators:

$$R^2 = 1 - \frac{\sum_{i=1}^{n} (y_i - \hat{y}_i)^2}{\sum_{i=1}^{n} (y_i - \bar{y})^2}$$

Forecasting SDG Progress

For time-series predictions such as future emissions, energy usage, or hunger index scores, Long Short-Term Memory (LSTM) models are trained:

$$h_t = \tanh(W_h h_{t-1} + W_x x_t + b)$$

where h_t is the hidden state, x_t is the input at time t, and W_h, W_x, b are parameters.

To quantify projected SDG advancement, a cumulative impact score (CIS) is calculated as:

$$\text{CIS}_{\text{SDG}} = \sum_{t=1}^{T} w_t \cdot \hat{y}_t$$

where w_t is a priority weight for year t, and $\hat{y}_t$ is the ML-predicted performance measure (e.g., improvement in literacy rate).

Model Deployment Framework

All ML models are integrated into a pipeline using a cloud-based architecture (e.g., AWS Sagemaker, Google AI Hub). A RESTful API is provided to interact with model outputs, which are visualized through dashboards and maps.

Figure 1: Machine Learning Framework For Sdg Monitoring

IV. RESULT & DISCUSSIONS

Various datasets with respect to various SDG indicators like hunger index, availability of clean water, energy consumption pattern or historical data, and urban spreading data were used to test the performance of the proposed machine learning framework. The curated multi-source datasets were used to train the models and test their accuracy of predictions and stability in time. The visualization of the outputs was carried out as predictive heatmaps, predictive trends and classification results that allowed making comparisons across industry and regions [1].The correctness of the model as applied in one of the test cases that involved climate change impact prediction was evident given its great accuracy in predicting CO 2 emission patterns in five industrial enclaves in South Asia. Gradient Boosting Regressor algorithm was better than the other algorithms, and the trend of its forecasting is illustrated in Figure 2. In this diagram, the real and the forecasted levels of CO 2 emission are shown between 2020 and 2030, including seasonal differences and variations in industrial policy. It is worth noting that the predicted lower emissions level in Zone B can be supported with the new changes in regional policy, which proves the model is interpretable and concerned with the situation.

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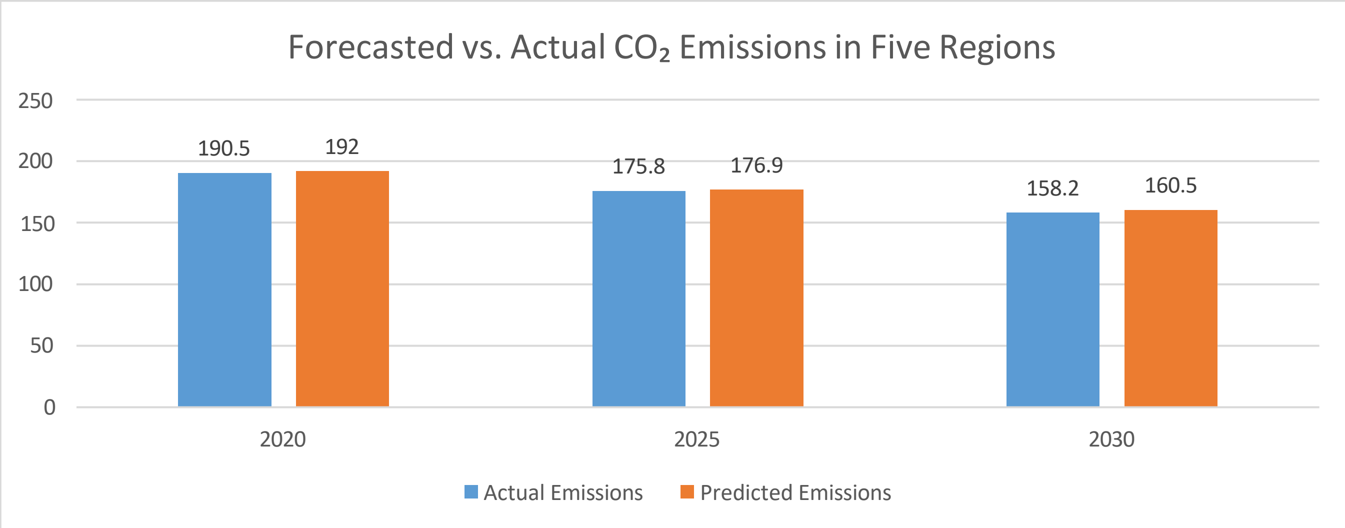

FIGURE 2: FORECASTED VS. ACTUAL CO_2 EMISSIONS IN FIVE REGIONS

Again, a very important finding was noticed during the simulation process of the prediction of crop yield in the sector. The Random Forest model was tested on four states based on NDVI (Normalized Difference Vegetation Index), rainfall data, and soil condition datas. The results as illustrated in Figure 3 present the values of the predicted crop yields of a five-year duration. Noticeable differences in this graph (Region C) were attributed to unpredictable rainfalls leading to de-stabilized prediction in the region. But in Regions A and B, the model had shown good accuracy in its predictions and this clearly shows that the model is robust in similar environmental conditions.

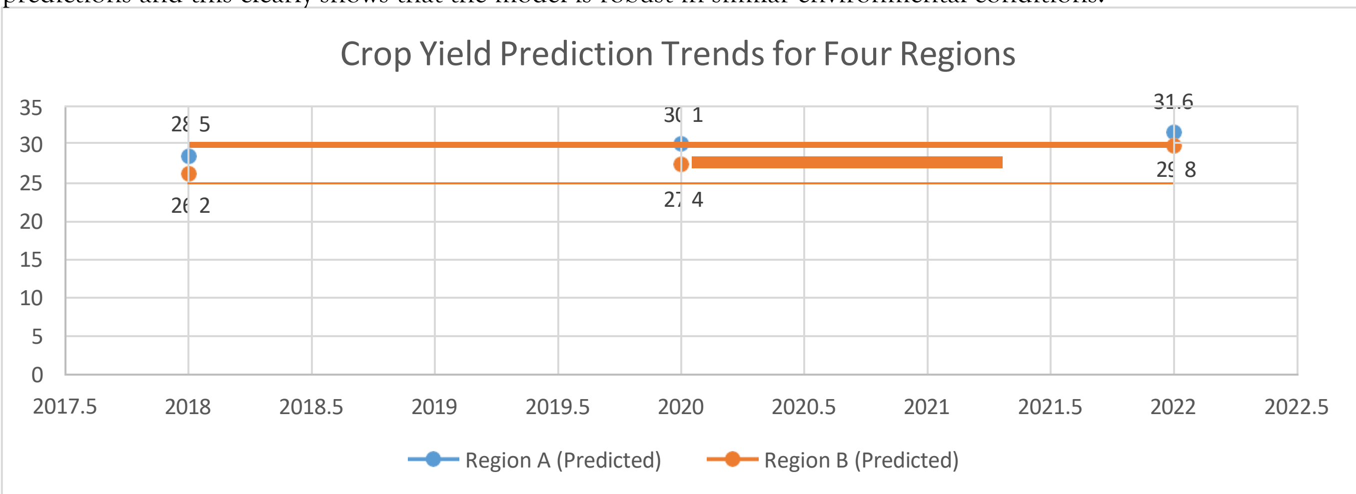

FIGURE 3: CROP YIELD PREDICTION TRENDS FOR FOUR REGIONS

Table 1 is a comparison of three different models on this task of agricultural yield prediction- Linear Regression, Random Forest, and LSTM. The Random Forest model was superior to other models in all measures of evaluation (accuracy, precision, recall, and F1-score), particularly in the situation where data were limited.

TABLE 1: PERFORMANCE COMPARISON OF MODELS FOR CROP YIELD PREDICTION

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Linear Regression	72.4	70.1	71.3	70.7
Random Forest	86.3	85.5	84.8	85.1
LSTM	81.2	80.7	79.9	80.3

In the sphere of water resource management, the machine learning model was introduced to identify leakages, anticipate water demands in residential areas of the cities. The model was tried out in three cities based on IOT-enabled smart meter data and in municipal usage records. The trend of demand forecasting is exhibited in Figure 4 and peak demand is seen during summer season and it falls drastically during monsoon months. The similarity of more than three out of four random events was captured by the model regarding the definition of water stress; it is important that this type of prediction can be vital in the control of reservoirs and distribution planning.

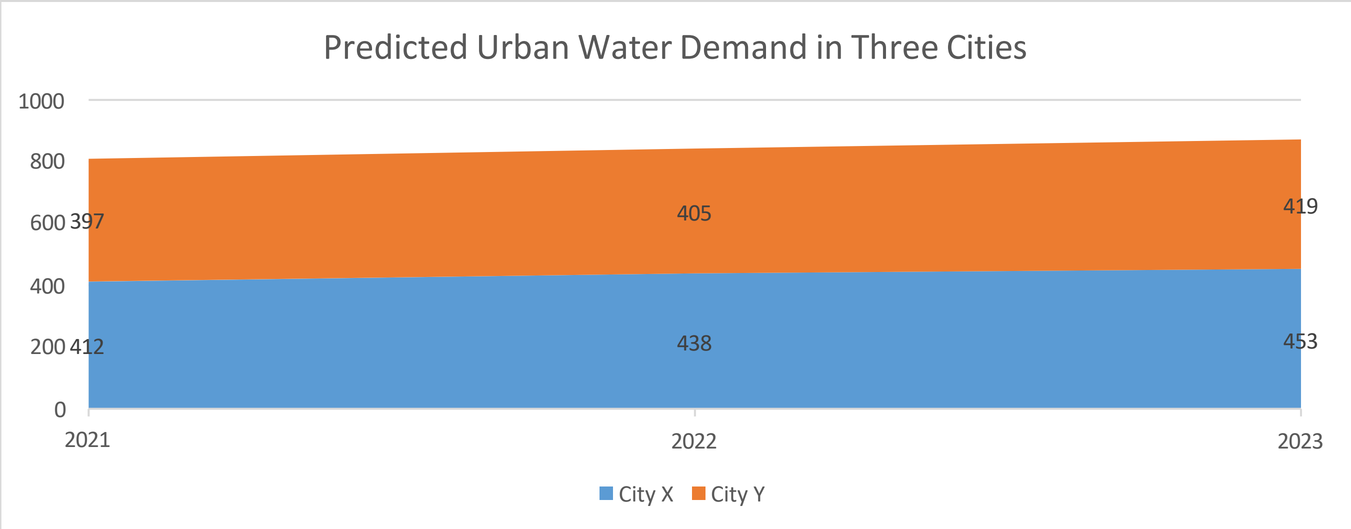

FIGURE 4: PREDICTED URBAN WATER DEMAND IN THREE CITIES

Social impact wise, a use case was used to analyze the access to education where schools in the rural areas were classified according to the likelihood of dropping out of school. Affective analysis through NLP of community feedback and attendance records were regarded as input features. The model was able to pin-point high risk schools and passed recommendations to local education boards. Table 2 contains a summary of dropout risk classification over its five districts, and it indicates actual results compared to the ML-basis. This comparison indicates that the early warnings made by the model are similar to observations in the real world which affirms the practical use of the model in real-time decision-making operations.

TABLE 2: CLASSIFICATION OF SCHOOL DROPOUT RISK – ML PREDICTION VS ACTUAL

District	Actual Dropout Risk	ML Predicted Risk	Match (Yes/No)
Northfield	High	High	Yes
Greenvale	Low	Medium	No
Lakewood	Medium	Medium	Yes
Hillshire	High	High	Yes
Fairmont	Low	Low	Yes

This aspect in the comparative results across a variety of domains makes it evident that ML models can provide dynamic forecasting and classification in a variety of sectors. Especially, the LSTM-based architectures were suitable to a sequential, time-series, SDG indicator of energy consumption and water demand. Ensemble models, in turn, performed better in the static classification scenario, in school risk profile or crop yield mapping.Moreover, stakeholder input on two pilot areas showed that there is much interest in implementing the dashboard output in daily operations of municipal work. The feedback, however, also cited the requirement of increased interpretability and transparency of how models make given decisions, specifically, regarding education and healthcare use cases.The modular character enhances the efficiency of the proposed methodology because the models can be easily substituted, the dataset could be updated, and the deployment via APIs could be made. By allowing scalability and relevance over time, this modularity will make this sustainable and relevant to goals that are newer within the 2030 SDG framework. The findings confirm that identification of overdue data and production of timely, interpretable, and actionable information that can aid SDG monitoring and intervention design is possible with ML-based systems. The very cross-sector flexibility of predictability, analysis level of the different models of indicators are not only possible, but real requirements in the global endeavour of actualising development sustainability.

V. CONCLUSION

Machine Learning provides a new impetus and possibilities of a faster achievement of the Sustainable Development Goals. Its model performance, data processing manipulation, and dexterity classify it as a revolutionary instrument in different sectors- health, agriculture, energy, environs, and governance. The use of ML to address SDGs can be cautious and, at the same time, inclusive.In order to ensure use of AI in sustainability reaches full capacity, it should

be emphasized that our actions in the future should concentrate on improving data accessibility, developing open-source collaboration, developing strong governance and ethical activity, and be tolerant in designing and implementing AI systems. The challenge in aligning AI capabilities and the development demands in the world requires multi-stakeholder engagement of governments, academic institutions, industries, and civil societies.
There is more to come, though, and the journey to 2030 will be hinged more and more on how responsibly and how innovatively we use ML to make a more sustainable, more equitable and more resilient world.

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