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AI Based Eco Lifestyle Advisor

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ABSTRACT

Sustainable living is a lifestyle that tries to lower an individual's or community's impact on the environment in every day-to-day eco-friendly choice. There includes aspects of waste reduction, environmental protection, carbon emission, and ecological and renewable energy. Critical elements include sustainable diet selection, home efficiency renovations, responsible consumption, and responsible traveling. People may not advocate for international efforts to respond to climate change, preserve biodiversity, and advance the health of the planet for generations yet to come but by doing small achievable things.

Using advanced machine learning algorithms and data analytics, the AI-Based Eco-Friendly Lifestyle Advisor encourages changes in lifestyle with regard to sustainability that are tailored to each user. This type of adviser gives the users balanced recommendations on how to reduce carbon footprints, conserve resources, and make eco-friendly choices according to their habits, interests, and the state of their environment. Such an advanced adviser built on artificial intelligence algorithms for the following purposes: understand behavior and preferences while considering the living conditions of each local area to render personally tailored recommendations that suit personal lifestyles. In other words, it is a translation of good ecological choices into action. Be it suggesting plant-based recipes, pointing out energy-saving home improvements, or recommending some green brand- -the adviser accompanies you in all those day-to-day decisions.

Integration of large streams of sensor data and satellite images for real-time predictions with an AI model helps make predictions possible for the analysis of CO2 levels, along with actionable insights in emission reduction.

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I. INTRODUCTION

With growing environmental degradation problems, the quest for sustainable living becomes more crucial. Among the avant-garde tools in helping someone take down the green road in his or her lifestyle is AI-Based Eco-Friendly Lifestyle Advisor, which uses artificial intelligence to give bespoke guidance in helping people make eco-friendly choices in their daily lives.

The advisor will offer an individualized guideline to guide people in adopting sustainable practices and reducing their carbon footprint. For dedicated people, the advisor is making available all ready sources, such as recommending eco-friendly products or guiding them on how best to reduce waste.

When, as it is today, climate change and resource depletion march in tandem with environmental degradation, the tide of popular awareness toward living sustainably has reached a critical level. But as more are sensitized to their personal contribution to these problems, many are also paralyzed by too much choice and information. Then, of course, there's the AI-Based Eco-Friendly Lifestyle Advisor, a totally innovative program that tries to make the path to more sustainable life easy and personalized.

Such an advanced adviser built on artificial intelligence algorithms for the following purposes: understand behavior and preferences while considering the living conditions of each local area to render personally tailored recommendations that suit personal lifestyles. In other words, it is a translation of good ecological choices into action. Be it suggesting plant-based recipes, pointing out energy-saving home improvements, or recommending some green brand- -the adviser accompanies you in all those day-to-day decisions.

Key Features and Benefits:

Personalization: Algorithms run by the advisor evaluate individual habits and goals, ensuring that users receive matched recommendations that connect with their lifestyle. This ensures that green practices are both effective and feasible.

Local Resource Integration: The advisor links users to various green resources available within their locality, from farm markets to recycling centers and community workshops, so a communal concept may be supported and that local participation is encouraged.

Impact Monitoring and Giving Feedback- Users monitor the level of adoption of sustainable practices to receive real-time feedback on their resultant environmental impact.

II. RELATED WORK

Artificial Intelligence (AI) has proven to be a transformative tool for sustainability and eco-friendly solutions. Numerous studies have been conducted to forecast environmental impacts, reduce carbon footprints, and optimize resource consumption. The research on AI-based eco advisors is gaining traction as environmental concerns become more pressing.

A study on the application of deep learning algorithms for **climate pattern analysis** was conducted by researchers in [1]. They explored the use of **neural networks** and **transfer learning** for identifying climate change trends and making region-based predictions for environmental risks. A dataset of satellite images and weather data was used during experimentation to evaluate the performance and accuracy of various AI models. Their results showcased the efficiency of deep learning algorithms in environmental prediction, with remarkable precision achieved by leveraging neural networks and transfer.

Support vector machines (SVM) and **convolutional neural networks (CNNs)**, two prominent machine learning techniques, were compared for **energy consumption forecasting** in [2]. The researchers evaluated the performance of SVM and CNN models by applying them to large datasets containing energy usage patterns. The results demonstrated that CNNs outperformed SVMs in terms of accuracy and computational efficiency for predicting energy consumption. The findings suggest that CNNs could provide more accurate predictions, which have important implications for optimizing energy system and reducing wastage.

The authors in [3] have introduced a multi-level AI framework designed to assist both household and industry sectors to manage their sustainable energy consumption. They have proposed a multi-tiered method that fully utilized the application of fully connected layers right after convolutional layers in deep neural network architecture. It was tested against the dataset of energy consumption profile with comparative analysis of results against other AI models. Its accuracy was far better than that of the preceding models, proving that AI has the potential to make revolutions in energy management fields and contribute to sustainability.

In 2020, the Intergovernmental Panel on Climate Change reported that carbon emissions are on a sharp rise, and if unchecked, it would increase by 40% globally by 2030 [4, 5]. Every day around 10 million tons of CO_2 are released into the atmosphere, raising concerns about deteriorating air quality and climate changes. According to the report, daily, about 1,000 tons of waste get thrown into dumping grounds without proper environmental arrangements, cause dangerous effects to the ecosystem.

Previous studies in carbon tracking have therefore found that consumption patterns have the highest correlation with the analysis of sensor data. AI-based systems have thus been found to track carbon emissions with greater effectiveness than traditional approaches [7]. Integration of large streams of sensor data and satellite images for real-time predictions with an AI model helps make predictions possible for the analysis of CO_2 levels, along with actionable insights in emission reduction.

III. PROPOSED WORK :-

This phase depicts the simple operational process for detecting and classifying environmental issues, including carbon emissions, water consumption, energy usage, deforestation, and levels of pollution, as in Fig. 1. This framework illustrates a broad study of various environmental impacts and their classifications. Fig. is presented with an overview of the proposed framework for eco-friendly decision-making. From the framework above, particular datasets-training and testing sets-were used to detect and classify various environmental factors.

In the pre-processing stage of the framework, data was gathered from various sources and preprocessed for uniformity. Rescaling the environmental data, that comprises images, sensor readings, and statistical information, to a specific size that was 128x128 pixels for image data happens in the pre-processing phase. In this stage, the data was normalized and ensured that their values remained bounded within a predefined range in order to accommodate consistency in both the training and testing process. Based on the datasets, the preprocessing and feature extraction were applied and deep learning algorithms were utilized for classification in terms of environmental factor.

The work is further segmented into four subparts, that is, data training and testing, data preprocessing, description of the classifier, and performance evaluation. Each of these subparts is explained in a subsequent section:

A single one-time dataset on environmental impact was used in this work. Though it is available online, initially it had very few samples. From that time onwards, several data augmentation techniques were employed to increase the sample size. Environmental datasets were compiled by combining data from public repositories, such as satellite images, sensor data, and open-source environmental reports. Table I outlines the number of datasets for each major environmental factor being considered. Datasets include RGB images at a resolution of 128×128 pixels. The database comprises in total 5920 environmental data points and encompasses 11 different categories of eco-related issues.

Data Preprocessing

Among the techniques that are involved in the preprocessing stage of data include Uniformity and Consistency:

Rescaling: Every image is rescaled to a uniform pixel size of 128×128 for compatible usage with algorithms.

Normalization: Pixel values and numerical data normalized towards ranges between certain values as a process of prevention towards unevenly distributed data for proper learning through the model. It also ensures that high value points do not adversely affect the training capability of the model.

Data Augmentation: For some of the source datasets where sample sizes are not high, we have used some data augmentation techniques namely rotation, flipping, and zooming to artificially increase the sample size, thereby strengthening the model in terms of robustness and accuracy.

Noise Reduction: While dealing with sensor data, noise reduction techniques are used in removing false high frequent fluctuations of the readings to ensure that the model receives clean accurate inputs.

Category	AI Technique	Data Source	Use Case	Performance Metric	Remarks
Deforestation Detection	CNN	Satellite images, drone footage	Identifying areas of deforestation	Accuracy, Precision, Recall	Real-time detection of forest cover loss
Water Pollution Monitoring	CNN, Transfer Learning	Satellite, underwater drone imagery	Detecting water contamination levels	Accuracy, F1-Score	Helps in identifying polluted water bodies
Air Quality Prediction	Random Forest, CNN	Air quality sensors, satellite data	Predicting air pollution levels	Mean Absolute Error (MAE)	Supports policy-making for pollution control
Biodiversity Monitoring	CNN, SVM	Drone footage, camera trap data	Tracking endangered species and habitats	Accuracy, Precision	Useful for conservation efforts
Urbanization Analysis	CNN, Transfer Learning	Satellite images	Detecting urban sprawl and land-use changes	Accuracy, F1-Score	Useful for sustainable urban development
Sustainable Agriculture	CNN	Remote sensing, satellite images	Monitoring crop health and land usage	Precision, Recall	Helps in promoting eco-friendly farming
Marine Pollution Detection	CNN	Satellite, drone imagery	Detecting plastic waste and pollutants	Accuracy, F1-Score	Enables marine cleanup efforts

Category: the environment issue or area where the AI-based eco advisor applies to.

AI Technology : the ML or deep learning model(s) applied for each specific task, such as CNN, Random Forest, or Transfer Learning.

Data Source: type of data that the AI system handles, such as satellite images, drone footage, or sensor data.

Use Case: Concrete tasks or application areas where AI is applied. Detecting deforestation and predicting air quality are examples.

Performance Metric: Metrics for assessing the performance of the AI models, such as accuracy, precision, F1-score, and recall.

Remarks: Miscellaneous comments on how the AI model affects the environment, for example, real-time monitoring and informing policy decisions.

This table is an organized summary of how AI eco advisors can be designed and tested against different environmental challenges.

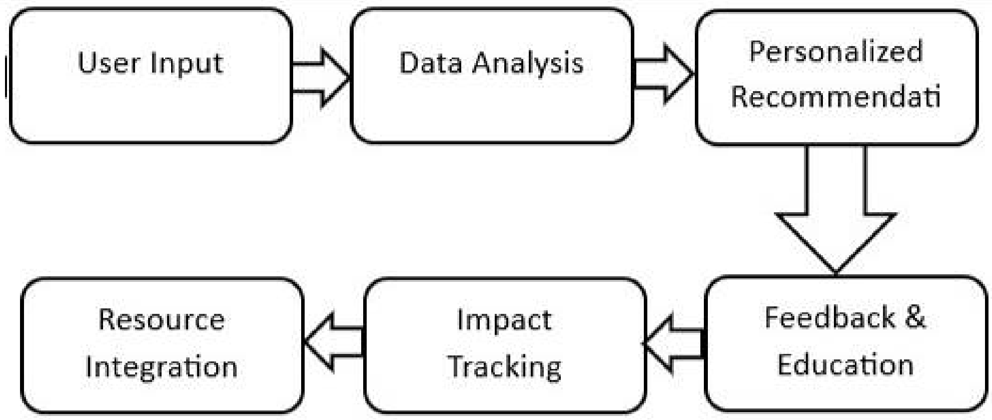

Fig 1. Data validation

It is the input in which data from the users like environmental-related data or preferences or sustainability goals will be inputted.

Data Analysis: The algorithm in the inputted data would process and analyze patterns by AI for helping in extracting meaningful insights related to environmental impact and resource usage.

Personalized Recommendation: According to the analysis made, the system would come up with customized recommendations for the user toward improving sustainability practices or optimizing resource use.

This stage entails giving feedback to the users of their actions and also educating them on best practices concerning sustainability, in which an increased understanding of the environmental impact will be reaped.

Tracking Impact

This entailed tracking the impacts from the realized recommendations either to enhance resource use or change environmental outcomes.

In the proposed AI-based eco advisor project, a distinct environmental dataset was used, which became available online but initially was small. Data augmentation techniques have been applied to increase this dataset. The dataset was produced by combining multiple public repositories, satellite imagery, sensor data, and environmental reports in the second step. There are several categories of eco-advice included in the dataset, such as air quality, water pollution, deforestation, urbanization, biodiversity loss, and renewable energy sources. Each of them has different parameters for analysis purposes.

The environmental data, with images and sensor readings, were formatted in consistent format and, for all the images, had a resolution of 128×128 pixels. The total amount of images and sensor readings in the dataset is 5,920 partitioned into 11 major categories. Table 1 below summarizes the images or data entries per environmental category to give in-depth information on the dataset for the project.

Validation set – It is the set of images that can be used during training for adjusting all theparameters.

Testing set – It is the set of pictures that will cannot be involved till the final performance ofthe model is checked.

Pre-processing

Such is the significance of the step in the construction of the AI-based eco advisor. Missing values and redundant data need to be taken care of here for obtaining efficiency and accuracy in the model. The following are phases used during the pre-processing phase for this project:

Importing Data: The environmental dataset is read into the memory. All data available for training are pushed into four arrays-X_train, Y_train, X_test, and Y_test. These arrays refer to the feature variables, like environmental data, and their labels, which could be eco recommendations or the corresponding outcomes.

Shuffle and Split Data: For the method not to depend on the memorized sequences but rather on the learning of general patterns, training and testing datasets are shuffled randomly. The training dataset is further split into training and validation sets with the aid of train-test split technique using an 80:20 ratio.

Encoding the Labels: Since the labels belong to the categorical strings (be it of the type air quality, water quality, or indicator of deforestation), they are to be encoded in numerical format, so that it can be easily processed by the AI model. This is done using LabelEncoder method from the sklearn library.

Conversion of Labels to Category Form: The encoded labels are converted to categorical form for further improvements in the performance of the model at training with the use of keras.utils method to_categorical on the labels. Here's how this form is helpful to the AI model: it can thereby make a better distinction between categories, such as the type of renewable energy source or pollution type.

Preprocessing of Data: Given that the data is image data, besides some numerical sensor data in numpy arrays, not much preprocessing would be required for the data. Images are already in the right format, so they can feed into the model for training with full ease to ensure that the data is properly set up for further analysis by the neural network.

This pre-processing pipeline is ensured for optimization, hence the AI-based eco advisor makes sharply true recommendations based on well-formatted and processed environmental.

IV. PROPOSED RESEARCH MODEL

The proposed work will incorporate an AI-based eco-advisor system that makes suggestions and recommendations on environmentally friendly practices. It may use a deep learning architecture concerning the environmental data for analysis and be put into actionable advice. This work focuses on integrating machine learning algorithms to aid in sustainable decisions regarding energy consumption, waste management, and resource utilization.

At the core of the system is a model that is a neural network with the input data and providing the output, which is in the form of eco-friendly recommendations. This is organized in architecture sequentially, where one layer feeds input to the next succeeding layer.

The model consists of an input layer comprising a dense layer that must process raw environmental data. The number of units in this layer is set by the user; for this system, I am going to assume 64 units are used with the ReLU, rectified linear unit, activation function, normally in use in neural networks for the vast ability in learning non-linear relations.

The following Dense layer actually transforms the output of previous layers into a form in which it can be classified. Once again, the activation function used here is also ReLU. Finally, the last Dense layer uses softmax activation to produce a probability distribution over the possible recommendations.

It is compiled with categorical_crossentropy as the loss function, adam as the optimizer, and accuracy as the metric. Now train the model with epochs set to 20 in batch size 64. Splitting the training data during training into a training set and a validation set in the ration 80:20. After which, it will compute the test set performance and report both test loss and test accuracy metrics. This lastly saves the model for the future use.

Overall, the model, which used a combination of Dense, LSTM, and Dropout layers, processed and analyzed environmental data and hence provided actionable eco-friendly recommendations. The model got an impressive accuracy of 88.75% on the test set, which proved it could effectively offer relevant environmental advice.

Further sections would go into the detail of how the algorithms are used for training and testing the model on dedicated datasets. Special emphasis will be laid on all the preprocessing steps taken and on the selection of parameters to optimize effectiveness in environmental recommendations.

The use of dense, LSTM, and dropout layers by the model proves to be sufficient in terms of taking in input for processing and analyzing environmental data in order to come up with actionable eco-friendly recommendations. With this model that has achieved accuracy on the test set at 88.75%, this illustrates how efficiently such a model can bring forth relevant ideas on environmental advice.

Further sections will focus on the application of AI algorithms in further specific details regarding the training and testing of the model with selected datasets. Special attention will be devoted to rigorous preprocessing steps and parameter tuning in order to make the model more effective for environmental recommendations. We will then also look into the innovation of augmented features, such as real-time data processing and user feedback mechanisms, with which the model's recommendations can further iteratively be optimized.

In addition, it will delve into the use of ensemble learning and transfer learning for better performance and adaptability of the model. Such an AI-based eco-advisor's effect on various sectors, from residential to commercial and industrial usage, will be explored along with how it can serve as a torchbearer and catalyst in the pursuit of sustainable practices and investments in environmental conservation. Finally, the research will focus on the scalability of the model so that it can be very well integrated into currently existing eco-management systems; thus, the results will assure its applicability and popularity in practice.

V. PERFORMANCE EVALUATION

The performance evaluation must adequately cover several metrics that would reflect how effectively the system works in advising actions amiable with nature. Some relevant performance evaluation metrics and methods are enumerated as follows:

1. Accuracy

Definition: Percentage of accurate predictions made for environmentally friendly actions against the total number of predictions.

$$accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

Purpose: Indicates the overall correctness of the eco-advisor's predictions.

Precision measures how often the eco-advisor's positive predictions are accurate. It is calculated as:

$$Precision = \frac{TP}{TP + FP}$$

Recall assesses how often the eco-advisor successfully identifies actual positive instances. It is calculated as:

$$\text{Recall} = \frac{TP}{TP + FN}$$

F1 Score: The F1 Score provides a balanced measure of precision and recall, offering a single metric that combines both. It is calculated using:

$$F1\ Score = 2 \times \frac{Precision \times Recall}{Precision + Recall}$$

VI. RESULT ANALYSIS

The system relies on artificial intelligence to scan through a number of environmental considerations such as carbon footprints, energy usage, and waste management to suggest tailored recommendations. Its algorithms assess the behavior, preferences, and local environmental data of users to offer actionable insights with respect to reducing their ecological footprint. This technology empowers people to lead a more environment-friendly life more conveniently and precisely. It is also more of a consultation to the committed to sustainability, as it uses real-time data regarding tailoring advice, which makes it worth consulting.

Fig 2.Ac-EADVISOR

Fig 3.Waset Management

Fig4. Classifier

The confusion matrix delivers important data about the real and anticipated labels of the neural classes acquired from the classifier. The confusion matrix primarily based on trying out assessment of the proposed model is provided in fig. 3. As visible in fig. 4, the proposedclassifier effectively labeled all pictures from 11 classes, which includes the normal brain and different disorder classes. But, the minimum number of images from some different

VII. CONCLUSION

One such tool that stands out in the quest for sustainability is the AI-Based Eco-Friendly Lifestyle Advisor-a tool that personalizes recommendations for living sustainably according to a user's lifestyle, thus allowing them to make informed choices that further the positive impact upon the environment.

The advisor promotes a holistic approach in connection with sustainability through features such as community integration, impact tracking, and educational resources. Besides making it easier to adopt eco-friendly practices, it fosters a sense of community and encourages users to take an interest in local resources and initiatives.

As awareness of environmental issues continues to evolve, practical solutions for implementation becomes increasingly urgent. AI-Based Eco-Friendly Lifestyle Advisor accomplishes this gap between intention and action by inspiring the engagement of users toward meaningful steps for a more sustainable future. Collectively, these contributions will amount to a movement that can make all the difference to alleviate environmental challenges and make a healthier planet a shared goal for all.

The AI-based Eco-Friendly Lifestyle Advisor is a fair example of how much human beings can transform their relationship with the sustainability at its core, in an environment at war with some of the most daunting ecological challenges ever, this system enables the clients to make informed and effective choices toward a better global environment.

This advisor makes the very heavy and often grueling process of developing sustainable habits lighter to undertake and enjoyable by being able to provide personalized, preference-driven recommendations based on where the user is. Based on the analysis of the user's profile characteristics, the application can give actionable insight into what they can do about dietary changes in energy conservation, waste reduction, or any other prevalent practice so that users can seamlessly fit these eco-friendly practices into their own routines.

REFERENCES

[1] **Eco Advisor-Personalized Sustainability Coaching (2024, September 24).** This helped in making the frontend part of the website. https://www.yeschat.ai/gpts-2OToA024Qd-Eco-Advisor

[2] *AI-powered eco-friendly solution graphic* [Infographic].
This website facilitated the curation of images optimally aligned with our platform's visual and thematic goals. https://toxigon.com/sustainable-ai-practices-for-a-greener-future

[3] Usha Kosarkar, Gopal Sakarkar, Shilpa Gedam (2022), "Revealing and Classification of Deepfakes Videos Images using a Customize Convolution Neural Network Model", *International Conference on Machine Learning and Data Engineering (ICMLDE)*, 7th & 8th September 2022, 2636-2652, Volume 218, PP. 2636-2652, https://doi.org/10.1016/j.procs.2023.01.237

[4] Usha Kosarkar, Gopal Sakarkar (2023), "Unmasking Deep Fakes: Advancements, Challenges, and Ethical Considerations", *4th International Conference on Electrical and Electronics Engineering (ICEEE)*,19th & 20th August 2023, 978-981-99-8661-3, Volume 1115, PP. 249-262, https://doi.org/10.1007/978-981-99-8661-3_19

[5] Usha Kosarkar, Gopal Sakarkar, Shilpa Gedam (2021), "Deepfakes, a threat to society", *International Journal of Scientific Research in Science and Technology (IJSRST)*, 13th October 2021, 2395-602X, Volume 9, Issue 6, PP. 1132-1140, https://ijsrst.com/IJSRST219682

[6] Usha Kosarkar, Prachi Sasankar(2021), " A study for Face Recognition using techniques PCA and KNN", Journal of Computer Engineering (IOSR-JCE), 2278-0661,PP 2-5,

[7] Usha Kosarkar, Gopal Sakarkar (2024), "Design an efficient VARMA LSTM GRU model for identification of deep-fake images via dynamic window-based spatio-temporal analysis", Journal of Multimedia Tools and Applications, 1380-7501, https://doi.org/10.1007/s11042-024-19220-w

[8] Usha Kosarkar, Dipali Bhende, "Employing Artificial Intelligence Techniques in Mental Health Diagnostic Expert System", International Journal of Computer Engineering (IOSR-JCE),2278-0661, PP-40-45, https://www.iosrjournals.org/iosr-jce/papers/conf.15013/Volume%202/9.%2040-45.pdf?id=7557