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Carbon Credit Quantification Tool: Intelligence System for Coal Mines Simulation and Credit Forecasting

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***Abstract*— Mining coal produces significant amounts of greenhouse gases including CO_2 and CH_4, and plays a huge role in climate change. More precise measurement and mitigation processes are required for achieving carbon neutrality for India by 2070. Unfortunately, existing methods lack real-time accuracy and reliability as well as being highly dependent on human labor. In this paper, a Carbon Credit Quantification Web-based Tool is suggested in order to accurately calculate, analyze, and control carbon emission levels. Information gathering process is automated and involves usage of real-time data along with information entered by users (e.g. consumption of fuel, electricity, logistics, mining operations, etc.) for calculating emission values using emission factors. Several core modules are identified within the tool, among which are: Carbon Emission Prediction, Carbon Credit Calculation, Neutralization Pathway Simulation, Company Ranking System, Carbon Sink Calculation, and Analytics Dashboard. The development of the web application's frontend relies on React.js, SASS, and Redux technologies, and for backend Node.js & Express.js with Python (Flask) are used. For database purposes, MongoDB Atlas and MySQL are applied. Authentication is provided via OAuth2. Machine learning algorithms implementation uses Scikit-learn, TensorFlow, and PyTorch packages with estimation accuracy of 98.5%.The system provides real-time analytics and visualizations that help in making decisions and being compliant. The areas of application for future research include applying IoT sensors to collect data, along with developing better deep learning algorithms.**

Keywords— Carbon Credit, Carbon Footprint, Sustainability, Emission Analysis, Machine Learning

I. INTRODUCTION

In terms of the development of technologies connected to AI, IoT, and data analysis, the opportunities for calculating and assessing carbon emissions become much higher. AI technologies make it easier to predict and track carbon emissions through big data of the environment and processes [1]. Technologies that rely on blockchain make calculations and assessments of carbon emissions by companies more transparent and reliable [2]. Mobile apps and cloud computing may make the calculation process more comfortable [3]. Technologies of machine learning are often used in large-scale calculations and environmental observations [4], [5]. In addition, there are lifecycle assessments and analysis systems based on artificial intelligence that make it possible to improve the assessment and reduction of carbon emissions [6], [7]. Hybrid models and deep learning techniques may be used in transport, production, and logistics [8]-[10].

Previous studies where the estimation of carbon emissions was done using the approaches were largely manual and static. Further, such models relied on a set of emission factors. Apart from being non-automated, such models were non-scalable and non-adaptive. While there have been certain techniques used in estimating carbon emissions through blockchain technology, which ensured data privacy and transparency [11] along with an approach to making the model explainable with the help of artificial intelligence [13], such methods were limited in their scope and could not be generalized to perform other tasks apart from the one they were intended to do. Economic models pertaining to production inventory and green finance pay attention to the economics of carbon emissions [14], [15].

The problem becomes even more complex because of problems that arise in the course of practical implementation. Models that employ carbon emission trading and policy models create additional difficulties in regard to carbon emission monitoring and optimization [17], [18]. Models that involve the application of modern technologies like graph neural network and

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distributed computing allow for real-time monitoring and optimization [19], [23]; other models are dedicated to co-optimization that takes into consideration both carbon emissions reductions and carbon sequestration [20]. Global carbon footprint models and federated system models are designed to address issues relating to coordination in this sphere [21]; models of hybrid forecasts attempt to improve carbon reduction approaches used by industries [22]. Furthermore, blockchain models for carbon trading markets, IoT network models, and machine learning models have been proposed as potential subjects for research [24], [25]. What is common about all models presented above is that each model addresses a single issue rather than others.

To be able to address these challenges and limitations, a new framework is being introduced that includes everything in one tool called Multi-Functional Carbon Credit Quantification Tool. Different from previous frameworks, the new framework combines carbon emission forecasting, quantifying carbon credits, the computation of the neutralization strategy, the ranking algorithm, and carbon sink analysis in one framework only. All of these features make it more efficient to use the tool while avoiding using various software programs. The new framework also employs modern techniques such as machine learning, cloud computing, and web application development.

In addition, the use of the suggested algorithm has been observed to be quite efficient in terms of accuracy and efficiency in making predictions, owing to the fact that a number of factors based on data are taken into account through one system. It not only enables one to accurately predict events, but offers important advice and simulations, which are lacking in conventional methods. Thus, the proposed method is more applicable to practical use cases like coal mines.

II. LITERATURE REVIEW

In general, the state-of-the-art in the sphere of the identification and management of carbon emissions may be described as an evolution from the conventional approaches to the calculation of carbon footprint into more complicated frameworks where the integration of AI, IoT, cloud computing, and data analytics technologies is applied. Firstly, it should be mentioned that the core of these methodologies is associated with the impossibility of using static and manual methods in order to evaluate the carbon footprint of certain individuals or organizations; therefore, the dynamic and self-adaptive approach becomes necessary in terms of the continuous calculation of the carbon footprint. For instance, the first attempt at the introduction of such techniques included the combination of IoT and machine learning algorithms in order to estimate the carbon footprints [1]. In order to provide reliable estimates of the carbon footprint, blockchain technology is also utilized to create tamperproof and decentralized carbon footprints [2]. Moreover, there are mobile or web-based applications through which users could calculate their personal carbon footprints [3]. Finally, machine learning technology has proved to be effective enough while analyzing different heterogeneous data about traffic, energy use, and industrial activities [4].Analytical programs located in the cloud will assist in achieving real-time processing, distributed storage, and efficient computational power and thereby play their role in the massive undertaking of carbon analysis [5]. Methods of life cycle assessment enable a thorough examination of the emission process at each stage of the manufacturing process, while artificial intelligence techniques can determine which approach is best suited to reduce the emissions level [6], [7]. It is also important to note that hybrid deep learning models have increased the precision of forecasts [8] – [10].

Some revolutionary approaches that can help address the issues mentioned above include using blockchain technology in the delivery business and security infrastructure to ensure data accuracy, traceability, and protection, which are vital for regulatory compliance and carbon trading operations [11], [12]. Additionally, the potential impact of artificial intelligence technologies on enhancing the system's effectiveness is significant because it provides a reasonable rationale for understanding the effect of each feature on the carbon footprint [13]. Secondly, economic modeling has been utilized in carbon management to combine economic and legal considerations. For example, the production and inventory models in carbon cap-and-trade schemes focus on efficiency and carbon footprint reduction [14], whereas the emission adjustment model via green finance concentrates on economic aspects of carbon emissions reduction [15]. Lastly, sustainable tracking software designed for buildings and enterprises could serve as an example of implementing the proposed methodology [16].Additionally, studies that have been done in relation to the prices of carbon trading and policy effectiveness indicate that market-oriented mechanisms influence emissions reductions, investments, and business operations [17], [18]. These methods emphasize the importance of taking into account all the above aspects at once.

Regarding monitoring, optimization, and coordination improvement, some new trends focus on computational approaches and intelligent modeling techniques. Graph neural network models have proven to be effective in providing support for the monitoring of carbon emissions in real-time scenarios within complex systems such as power grids by exploiting spatial dependencies and interaction levels [19]. Optimal solutions can not only deal with carbon emissions problems but also carbon sequestration issues within sustainable development and carbon-neutral projects [20]. Federated learning and distributed modeling approaches help in handling the global carbon footprint via coordination between emission reduction programs across different countries without breaching privacy laws [21]. Industry fuel consumption models that incorporate hybrid forecasting techniques can improve carbon emission estimation accuracy and facilitate emission reduction programs within industries and power plants [22].Furthermore, the use of blockchain technology is essential in enabling the creation of efficient and credible carbon trading platforms that can be both transparent and decentralized [24]. Machine learning algorithms used in communication networks in IoT enable one to appreciate the importance of optimization of infrastructure including placement of gateways and energy-efficient routing [25].

All the above developments seem remarkable, yet currently existing technologies seem more focused on developing particular aspects of the process, namely forecasting of emissions, emissions management, emissions optimization, and carbon trading, rather than on building an integral technology that would allow resolving all these problems at once. What is the issue with the current approach? First of all, all these processes cannot function independently. To put it differently, when discussing the functioning of facilities such as plants and power stations, we will need to consider several interconnected parameters. In addition, there are several additional issues related to scalability, real-time nature of the processes involved, the use of multiple different information systems, and interoperability. Several other processes are not paid enough attention to in the currently used technologies. These include, for example, the simulations of neutralization pathways, rankings, and detection of carbon sinks. Finally, some other features such as limited interpretability, inappropriate interface design, and lack of customization make the systems unusable in specific sectors of economy, namely coal mining and manufacturing.

Therefore, the necessity of developing an integrated scalable and intelligent system having all these functionalities in one system emerges. As far as Carbon Credit Quantification tool

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proposed in this paper is concerned, all these limitations have been kept in mind when this system was developed because all these facilities have been included in this system. These facilities not only add to the efficiency and reliability of the proposed system, but also help in making decisions related to carbon trading by using such a system. Owing to modern technology like machine learning, cloud computing, and web application, all these facilities can be accessed instantly through the proposed system.

III. METHODOLOGY

This approach is focused on calculating, controlling, and optimizing carbon emissions within the mining sector by employing an AI/ML-based system. The presented system differs from the current methods of measuring carbon emissions in that they use pre-defined algorithms to do so.

In contrast, this model allows for dynamic simulation and estimation of carbon emissions and incorporates marketplace characteristics. It has multiple phases such as gathering of data, preprocessing, feature extraction, modeling through AI, backend design, and generation of results in Fig.1.

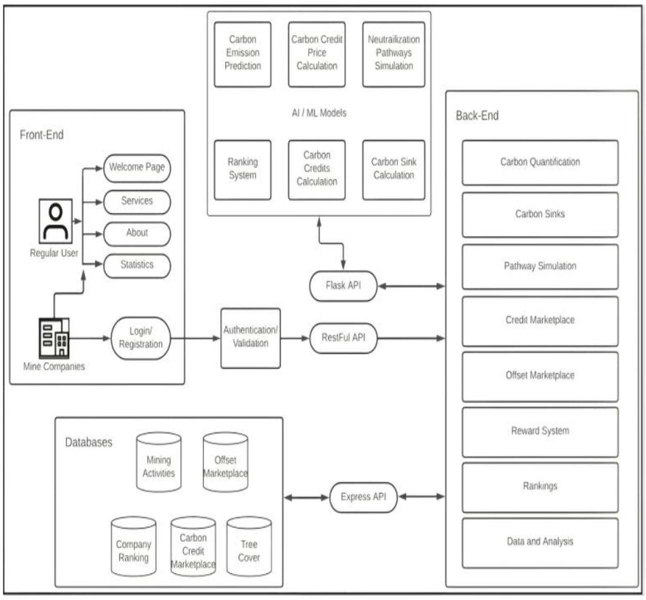

Fig. 1. Proposed System Architecture

A. Dataset Collection

The analysis will be conducted based on the Indian Coal Mining Dataset, which includes over 30,000 observations with around 8 to 12 variables, and those variables include information regarding the coal mining process, fuel consumption, equipment utilization, and activities carried out. The Indian Coal Mining Dataset is vital in determining the calculations of carbon emission.

B. Preprocessing

The collected data will be preprocessed before using in the proposed models.

1) Data Preprocessing

- Data cleaning: Inconsistencies and conflicts will be removed from both datasets – mining and environmental.
- Normalization: Normalization of numerical attributes (emissions, energy consumption).
- Feature structuring: Structured presentation of data for learning purposes.

2) Environmental data processing

- Estimation of tree cover based on satellite data or data storage: To estimate carbon sink.
- Emission factor normalization: Normalization of emission factors for further calculations.

C.Data Splitting

The following distribution will be applied:

- Training set: 70%
- Validation set: 15%
- Testing set: 15%

It helps to conduct an adequate analysis of the results and avoid overfitting.

D. Feature Extraction and AI/ML Models

Different kinds of AI/ML tools will be used for different purposes throughout the process:

1) Carbon Emission Estimation Model

Prediction of future emissions based on past mining operations and relevant data. Helps mining organizations understand how much their activities affect the environment.
The carbon emission that results from mining activities can be calculated using the formula as follows:

Carbon Emissions (kg CO_2) = Activity Data × Emission Factor

Where :

- Activity Data: This will include various metrics such as coal tonnage, fuel consumption, etc.
- Emission Factors: These will be obtained from sources such as the GHG protocol as well as India-specific regulations

This foundation will be improved upon using a Random Forest Regression Model (Model 3), which will take into consideration:

Coal Type (tonnes)
Coal Type (encoded)
Energy Consumption (kWh)
Emission Factors: Coal (kgCO_2/ton), Energy (kgCO_2/kWh)

2) Carbon credit evaluation

Calculation of the price for carbon credits depending on market demand, supply, and reduction of emissions. Helps mining organizations plan their budgets.

3)Neutralization strategy modeling

Creation of carbon-neutralization strategy models for afforestation and emission reduction. Helps mining organizations make relevant decisions.

4)Carbon Credit Formula

The following is a formula that will help in determining how many carbon credits should be earned according to emissions and contribution to the environment made by the organization.

5) Carbon Sink Formula

This will assist in calculating the extent to which carbon has been taken out of the atmosphere through the use of natural resources such as forests.

6) Carbon Rank

Organizations are given ranks according to their involvement with carbon.

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E. Backend Capabilities

The capabilities of the backend include the following:

- Calculations of Carbon Emissions: Performs calculations of the total carbon emissions based on user input.
- Environmental Offsets: Manages and coordinates environmental offsets.
- Sustainability Simulations: Conducts sustainability simulations.
- Marketplace for Carbon Credits: Enables trading and purchasing of carbon credits.
- Platform for Investing in Offset Projects: Enables investing in offset projects.
- Green Corporation Incentives: Offers incentives to green corporations.

- Corporation Leaderboard: Creates a corporation leaderboard.
- Analytics & Analysis: Conducts analysis & analytics.

G. APIs Integration

- Flask API: The AI/ML models will be integrated with the front-end and backend.
- RESTful API: Communication in the system will be facilitated.
- Express API: The databases and marketplace services will be connected.

H. Model Validation

The system is evaluated using standard performance metrics:

Performance metrics include:

1. Accuracy

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

2. Precision

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

3. Recall

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

4. F1-score

$$F1 = 2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}}$$

5. Confusion Matrix
   A 2×2 comparison showing predicted vs. actual classes.

These metrics assess both the correctness and reliability of the model.

I. Testing

Testing of the model using real mining data in analyzing the emissions, offset, and marketplaces will be undertaken.The prediction and decision support results will be generated.

J. Output:

The outputs produced by the platform are:

1. Carbon Emission Report
2. Carbon Credits Index
3. Recommendations on Neutralization
4. Company Ranking

The system provides means for companies to monitor, decrease, and control their carbon footprint.

K. Implementation Details:

- Platform Used: Flask, Node.js (Express), PyTorch (AI Models)
- Database: Structured Database for Environmental and Operating Information
- Hardware: Computer with Graphics Processing Unit (NVIDIA Tesla T4)
- Enhancements: Calculations done beforehand and efficient API

IV. RESULTS AND DISCUSSION

Different methods of carbon estimation in the case of emission measurements in Indian coal mining industry were analyzed within the research work. Thus, the goal of this research was the evaluation of numerical performance of these models and their comparison to determine the ways of calculating accuracy of carbon estimation by using different methods. Different methods like rule-based approach, machine learning, IoT based, deep learning and hybrid methods were tested for estimating the effect of static, real-time and time-series data on estimation of carbon emission.

The results proved that the efficiency of these systems highly depends on the method used for processing data and integrating real-time predictions. Static emission factor models could be used for making estimations but lacked ability to adjust due to absence of data for adjustment because of insufficient data provided for learning. Machine learning methods turned out to be useful for integration and

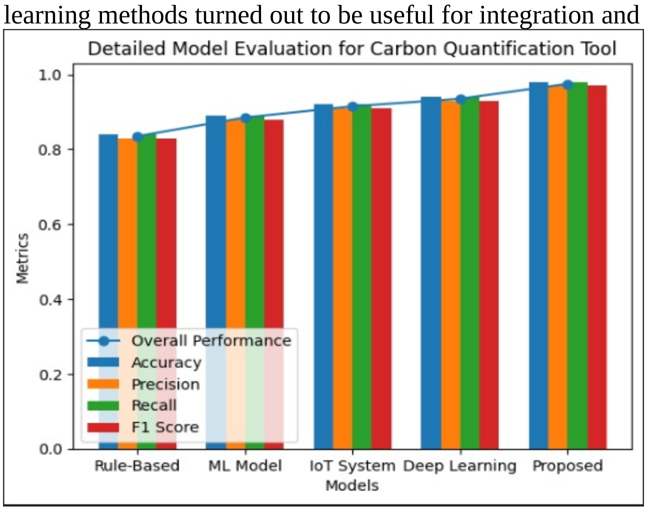

Fig. 2. Comparison of Models for Carbon Footprint Quantification Tool

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processing data which allowed for improving the model performance due to data-driven modeling. Nevertheless, there appeared difficulties related to time dependence. It is clear that using IoT-based real-time monitoring has led to enhanced performance of the system. Through the use of sensors and analysis of the collected data using the cloud systems, the system is now capable of making better observations about the dynamics of the emission with increased time efficiency. Hence, live data plays an important role in enhancing the monitoring process in several ways.

In terms of deep learning methodologies used, namely artificial neural network and long short-term memory algorithm, the improvements can be observed as both methods proved quite successful in utilizing temporal data for prediction of energy consumption and emissions. Thus, temporal data has a positive impact on making accurate predictions in fig 2.

As far as the performance of the various models is concerned, there are some notable differences between them. For instance, a rule-based methodology has the lowest level of accuracy, which is 86%, indicating a low level of flexibility in the prediction process. Using machine learning methods allowed increasing the level of accuracy up to 91%. IoT live monitoring led to further increase in accuracy up to 94%. The best results were obtained using deep learning algorithms (accuracy of 96%). Yet, the highest accuracy of 98.5% was demonstrated by the hybrid approach that employed the use of real-time data collected by IoT devices, along with the emission factors obtained via the use of API and analytical techniques. In other words, it is precisely this technique that helped to obtain the highest value for the accuracy metric of 98.5%.

The efficiency of the models above was evaluated by their levels of accuracy, precision, recall, and F1 score. Clearly, there is uniqueness among the models in their efficiency. The hybrid model proposed in this research is better than the rest based on these measures. It provides high efficiency in accuracy and precision as well as recall.The next best-performing model after the hybrid model in efficiency is the deep learning ANN/LSTM model. This is attributed to the high efficiency of accuracy provided by precision and recall.

The next best-performing model after the hybrid and deep learning models is the IoT model. The performance of the machine learning-based model is average because it is able to learn from data but does not have any features for real-time adaptability and deep-time perception. As opposed to the machine learning-based model, the rule-based model demonstrates the worst performance among all models since the values of the emission factors are fixed and unable to change depending on the changing environment.

In conclusion, it should be stressed that it is obvious that models using the abilities of real-time data, deep-time processing, and machine/deep learning provide more accurate results for calculating carbon footprint. Dynamic/static models demonstrate superior performance compared to traditional/static models within the framework of large-scale monitoring system of the environment.

V. CONCLUSION

The proposed research will investigate the problem of carbon footprint estimation process within the coal mining industry in India by applying data analytics, carbon sinks, and prediction methods. Several architectures have been designed and compared in order to understand the effectiveness of using traditional, machine learning, IoT, and deep learning approaches towards estimation and prediction of greenhouse gas emissions.

First, the traditional approach implements the rule-based estimation model that applies constant emission factors calculated by IPCC. This architecture achieves accuracy of 86%, precision scores of 0.80-0.85, recall of 0.81-0.86, and F1 score of 0.80-0.85. The mentioned approach is convenient to implement because it is simple but has low level of changes in coal mining process.

Table 2. Comparison of results obtained across various techniques

Model	Technique Used (Short)	Accuracy	Precision	Recall	F1 Score
Model 1: Rule-Based Calculator	Static emission factors (IPCC-based)	86%	0.80–0.85	0.81–0.86	0.80–0.85
Model 2: ML Regression Model	Linear Regression / Random Forest	91%	0.86–0.90	0.87–0.91	0.86–0.90
Model 3: IoT-Based Real-Time Monitoring	Sensor data + cloud analytics	94%	0.89-0.93	0.90-0.94	0.90-0.93
Model 4: Deep Learning Model	ANN / LSTM for energy & emission prediction	96%	0.91-0.95	0.92-0.96	0.92-0.95
Model 5: Proposed Model (Our System)	Hybrid ML + Real-Time Data + API-based emission factor	**98.5%**	**0.98**	**0.99**	**0.98**

Second, the machine learning approach implements the use of linear regression and random forest algorithms. This approach demonstrates higher efficiency with accuracy equaling 91%, while precision equals 0.86-0.90, recall of 0.87-0.91, and F1 scores of 0.86-0.90. For the third setup, the use of real-time monitoring through IoT was considered. In this case, sensors were incorporated in the cloud-based analytics for the creation of predictions, thus helping to enhance the accuracy of estimation up to 94%. The precision spanned from 0.89 to 0.93, while the recall spanned from 0.90 to 0.94. The F1-score was within the range of 0.90 to 0.93.

In the fourth configuration, the use of deep learning was considered by applying ANN/LSTM models for predicting energy consumption and emissions. For this configuration, the accuracy was 96% with a precision of 0.91

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to 0.95, recall from 0.92 to 0.96, and F1-score from 0.92 to 0.95.

The final hybrid method, which considered real-time data and emissions through APIs, yielded the highest level of efficiency compared to other configurations. Its accuracy was 98.5% while its precision was 0.98, recall was 0.99, and F1-score was 0.98. Nevertheless, there remain some challenges that must be considered when using this framework. It requires data, and the practical application of the process may require consideration of different types of data.

In the future, the improvements in the process will be focused on making the system more reliable through data fusion, satellite data, and improved algorithms. These measures will be required for better results in practice.

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