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Corrosion Analysis Tool Using Pencil Graphite Electrode Sensor with Machine Learning Algorithm

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Abstract

Corrosion is an electrochemical reaction that leads to the deterioration of metallic materials, posing significant challenges across various industries. Traditional corrosion analysis methods require manual data collection using electrode sensors and laboratory-based analysis, limiting automation, mobility, and predictive capabilities. To address these issues, a Corrosion Analysis Tool was developed using a Pencil Graphite Electrode Sensor in combination with machine learning algorithms. The tool integrates regression analysis to enhance data integrity, automate predictions, and minimize human errors. Cloud computing is employed to replace traditional physical servers, facilitating remote access and real-time analysis. A mobile application is also developed to provide users with a convenient and efficient corrosion analysis platform. The system was evaluated by comparing its corrosion rate analysis results with traditional laboratory experiments conducted by chemical science students. Results demonstrated high accuracy, with minimal deviations between the corrosion rate values obtained from the Corrosion Analysis Tool and manually computed rates. The differences observed were 0.236×10^{-8} for a 7-day immersion, 0.049×10^{-8} for a 14-day immersion, 0.071×10^{-8} for a 21-day immersion, and 0.014×10^{-8} for a 28-day immersion, confirming the system's reliability. The precision test further verified that the tool effectively reduces human errors and enhances data integrity. Furthermore, the tool streamlines project management by centralizing data storage and organization, preventing data redundancy and loss. In conclusion, the Corrosion Analysis Tool successfully automates corrosion analysis, improves mobility, and enhances data-driven decision-making for researchers. The system meets all user requirements, offering a robust solution to traditional corrosion analysis challenges. Its predictive capabilities, powered by machine learning, provide valuable insights for future corrosion prevention strategies. By incorporating cloud-based storage and mobile accessibility, the tool modernizes corrosion analysis and contributes to advancements in materials science and engineering.

1. Introduction

In the contemporary business landscape, thriving organizations cannot afford to overlook significant instances of corrosion failure, particularly those that result in human harm, loss of life, unplanned cessation of operations, and environmental pollution. Corrosion may result in breakdowns in plant architecture and machinery, which often incur significant expenses for repairs, losses in terms of product contamination or loss, environmental harm, and even risks to human safety [1]. Corrosion is a process of the deterioration of metals [2]. When a metal undergoes a chemical reaction with the atmosphere or environment around it, corrosion happens [3]. The effect of corrosion may bring harmful potential to the environment. Because of this, buildings [4] and bridges may collapse [5], [6] , pipelines may be damaged [7-9] and chemical plants may leak [10]. There are several methods to measure the corrosion rate of a material. One of the most conventional techniques was using electrochemical-assisted measurement [11], in which, in this case, potentiostat and electrodes were used [12-13]. Pencil graphite electrodes are an excellent sensor for electrochemical sensing because of their features, which are that they are reliable, feasible, disposable, and inexpensive. These electrodes have been found to be extensively valuable for detecting environmental contaminants due to their ease of fabrication.

The outcome of the study heavily relies on the pre-treatment of the active region of the electrode, which is influenced by the hardness of the pencil lead and the efficiency of electron transmission. Biosensing investigations of pesticides and medicines, in particular, use the pencil graphite electrode. Sensing techniques using a pencil graphite electrode are more cost-effective, have more selectivity, and are more sensitive. Eliminating the influence of corrosion in the measurement of analysts with excellent repeatability was made easy with the easy polishing of produced pencil graphite electrodes [14]. The preparation of pencil graphite electrodes is simplified by the material's ready availability and renewability. The pencil is a widely used tool that is portable, inexpensive, and made of graphite. It is available in several sizes and lengths and can be found all over the globe. The ability to extrude leads to any required length from the pencil holder being effectively used in pencil graphite electrodes. Following each electrochemical assessment, the used surface might be effortlessly rejuvenated by eliminating the extruded portion. Furthermore, the portion of the pencil that comes into contact with the solution may be readily regulated based on the study of the requirements [15]. The current inefficiency of electrochemical-assisted measuring methods used by contemporary researchers is mainly attributed to the absence of automation. To determine the corrosion rate, data collected from the cyclic chromatogram, along with the measured metal concentration, are used in a specific formula to calculate the corrosion rate.

However, with the help of apparatus, the researchers need to analyze the data manually. After the user transfers the data to the computer, the user will need to open an Excel program to visualize and read the data value from the graph plotted. This will cause some systematic errors that will lead to an accurate result. It is also impractical to do corrosion analysis using a potentiostat microcontroller in field studies because researchers need to carry the equipment and data here and there; hence, the process could be more convenient. In the meantime, the current method did not propose any solution for predicting the corrosion rate for future studies [16]. The objective is to analysis corrosion using Pencil Graphite Electrode Sensor with Machine Learning Algorithm

2. Existing Systems and Related Work

There are three existing systems: the Corrosion Monitoring System by Matergenics, the S.P. Corrosion Study system, and the OLI studio corrosion analyzer. The individualized corrosion monitoring system from Matergenics is intended to gather and assess corrosion data originating from underground or above-ground facilities, process lines, or cathodic protection equipment situated at the location of the project. Furthermore, this data can be transmitted automatically to the web data centre. Alert messages are generated to notify of changes in conditions at the site, while routinely scheduled measurement data is gathered to archive the performance of the cathodic protection system on a system-wide scale. Consequently, users are granted the ability to retrieve historical corrosion data and observe graphical representations of corrosion processes [17]. Metagenics is an organization that emphasizes the evaluation and provision of user-friendly wireless and online devices. These devices can offer performance metrics, monitor activities throughout the day, and incentivize organizations to prioritize network and subterranean asset maintenance. Their system, according to Matergenics, is an internet-based view of information about the system that enables businesses and individuals to monitor and administer their assets more effectively. Furthermore, S.P. Corrosion Study is a mobile application developed by SPTech. It is an application that is designed to study the corrosion rate in an aqueous marine environment. The application comes with a simple user interface that allows a user to choose the data format for data input. Then, the user must manually insert its data value to process the corrosion analysis calculation. It comes with a straightforward interface that allows users to use it effortlessly. Besides that, SPTech also provides a web-based system for corrosion consultation service, which offers more functionality than the mobile application. On the web-based system, it gives more corrosion-related information. Including an online consultant between their trained expert who promise to study the user problems and perform testing and research by using computer modelling to estimate the life of the structure, but it is not counted as an automated process because it requires an expert from SPTech to serve a user with their provided services [18]. The OLI Studio corrosion modelling programme from OLI System, Inc. includes the Corrosion Analyzer subsystem. General corrosion rates, alloys' inclination to localized corrosion, heat-treated alloy depletion profiles, and metal and alloy thermodynamic stability are all predicted using this method. With its help, users may pinpoint the mechanical factors that cause aqueous corrosion and take action accordingly. Consequently, consumers make educated decisions on how to lessen or do away with this threat. The OLI Studio is an offline computer-based execution program that requires users to install it on their computer. The program predicts corrosion rates with a limited set of chemistry data using an algorithm that is kept confidential by the OLI System. This means that to get updated chemical information, a user needs to wait for the next update patcher. All user data is stored in local memory, and the program is only used for execution without connecting to the Internet [19]. Table 1 below shows the summary of the existing system.

Table 1 *Comparison of existing system*

System / Feature	Matergenics Corrosion Monitoring System	SP Corrosion Study System	OLI Studio Corrosion Analyzer
Platform	Web and Mobile	Web and Mobile	Executable
Cloud Computing Support	Yes	No	No
Project Management Service	Yes	No	Yes
Artificial Intelligent Support	No	No	No
Way to predict corrosion result	Based on algorithm	No	Based on algorithm
Data Visualization	Yes	No	Yes
Ease of Use	Only usable when integrate with Matergenics system. Need to attend tutorial course before use.	Able to make some basic calculation or analysis with simple interface but come with limited features	Able to perform various analysis and calculation but with limited set of data information.
Storing Data Feature	On Matergenics Server	Not Supported	On local storage

As can be seen, each of the existing systems has its own set of features. The main idea of the studied application is to let the user perform the corrosion analysis process. In terms of mobility, both the Matergenics Corrosion Monitoring System and the S.P. Corrosion Study System can perform corrosion analysis on the go. Still, Matergenics Corrosion Monitoring System is only compatible with their own system's sensor to sense results from the target. Matergenics Corrosion Monitoring System is capable of displaying results only, and a user cannot perform any interaction with the interface. Next, S.P. Corrosion Study System has a more manual control type of interface, and it operates like a scientific calculator. It does not support any sensor for retrieving data. Hence, the user needs to retrieve data from a third-party sensor that is independent of the S.P. Corrosion Study System application and manually enter the data into the mobile application to perform corrosion analysis. In terms of corrosion data prediction, three of the existing systems mentioned above need to integrate machine learning techniques to perform data prediction. However, Matergenics Corrosion Monitoring System does provide the prediction feature by using unique algorithms developed by their expert corrosion engineers. Lastly, OLI Studio Corrosion Analyzer also provides a prediction feature by using specific algorithms which are kept confidential by their company [20]. Next, in terms of user usability, the Matergenics Corrosion Monitoring System is the most complex among 3 of the existing systems. Before using any system provided by Matergenics, the user needs to make an appointment with their consultants to join their training and educational seminar because they want their users to have a good experience when using their service [21]. For OLI Studio, there is a user guide to teach the user all the steps needed to perform corrosion analysis in their system. Overall, the S.P. Corrosion Study System will be the easiest to use, but the downside is it comes with a limited set of features. If the user would like to perform a more advanced method of corrosion analysis, the user needs to contact their expert team to arrange a consultation session. Hence, it could be more practical and convenient when a user needs more analysis services in S.P. Corrosion Study System. Finally, in terms of cloud computing services and data storage management, the S.P. Corrosion Study System and OLI Studio do not implement cloud computing techniques in their system.

In the Matergenics Corrosion Monitoring System, Matergenics has a cloud server for data storage and analysis functions. S.P. Corrosion Study System does not have any capability for data storage; it is purely a calculator for the user to enter the value and calculate the result based on some preset formula, and the data will be erased after each session. Lastly, OLI Studio offers a data storage feature that stores data on the user's local storage in CSV format.

2.1 Existing Machine Learning Analytic Algorithm

A subfield of artificial intelligence, machine learning enables unprogrammed computer programs to acquire knowledge from data and enhance their precision progressively. For this undertaking, the established regression analysis algorithm will be utilized due to its capacity to generate output predictions from continuous numerical inputs. Regression algorithms belong to the category of algorithms that are supervised in machine learning. The prediction of target values for new data inputs is contingent upon the interdependencies of the method's model and the relationships between the goal input and output features [22], [23], [24]. Three machine learning models are usually used: simple linear regression, Lasso regression, and ridge regression. A straightforward algorithm, the simple linear regression model predicts the relationship between two factors or variables. The dependent variable is the factor whose value is being predicted, whereas the independent variable is the factor whose value is being used to predict the dependent variable. A regression line may indicate the absence of a relationship, a positive linear correlation, or both [25]. The possibility that the data points do not establish a cause-and-effect relationship is a constraint of simple linear regression. Further investigation and statistical analysis will be required for the researcher to ascertain the precise nature of this relationship and ascertain whether one variable is responsible for the other, Lasso is an abbreviation that represents the Least Absolute Shrinkage selection operator.

As an alternative to traditional regression methods, the lasso regression method is a regularisation technique that improves prediction accuracy. This model reduces data values to a central point, which serves as the means, using the contraction technique. Lesson-sparse models, such as those with fewer parameters, are encouraged by the lasso procedure. When particular aspects of model selection, such as selecting variables or parameter elimination, require automation or when models exhibit significant multicollinearity, this type of regression algorithm is highly suitable [26].

On the other hand, the ridge regression technique is utilized when multicollinearity is present in the data. L2 regulation is executed by this algorithm in the presence of multicollinearity, unbiased least square value, and significant variances. This problem will significantly deviate the predicted values from the observed values. A cost function incorporating a regularisation term into the algorithm compels the model to assign the minor possible weights to its parameters. In contrast to the standard linear regression model, lasso regression and ridge regression pertain to the linear regression family. This must be taken into account when contrasting the three. Linear regression in Sci-kit Learn utilizes the most standard least-squares linear regression technique, which does not employ any form of regularisation. Not all three of them penalize the algorithm for its weight, which is the primary distinction between them. Consistent with previous statements, linear regression represents the most fundamental type of regression algorithm in which the model's weight selection does not incur any penalty. As a result, when this algorithm is being trained on a short dataset, the model may conclude that a single feature is especially significant and assign it a disproportionate amount of weight, which can lead to overfitting. Lasso regression is an algorithm developed to address this concern. Table 2 summarized comparison of Simple Linear Regression, Lasso Regression, and Ridge Regress.

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Table 2 *Comparison of existing machine learning*

Regression Model	Description	Key Features	Limitations	Use Cases
Simple Linear Regression	Predicts the relationship between two variables (one independent, one dependent) using a linear equation.	- Basic regression model - Establishes correlation between variables - No penalty on model weights	- Cannot establish cause and effect relationships - Susceptible to overfitting with small datasets	- Basic trend analysis - Initial exploratory studies
Lasso Regression (Least Absolute Shrinkage and Selection Operator)	A regularization technique that shrinks less important feature coefficients to zero, effectively performing feature selection.	- Reduces data values toward a central mean - Useful for sparse models - Automatically selects important variables	- May eliminate some relevant variables - Struggles with highly correlated predictors	- Feature selection - Models with many irrelevant predictors
Ridge Regression	A regularization technique that applies L2 penalty to shrink coefficients, preventing overfitting.	- Addresses multicollinearity - Reduces model complexity - Prevents overfitting	- Does not perform variable selection - All variables contribute to predictions, even if some are less significant	- Handling multicollinear data - Improving model generalization

2.2 Existing Method for Corrosion Measurement

Corrosion measurement involves a broad range of techniques and methodologies. The use case employs potentiodynamic polarisation techniques, including potentiodynamic polarisation, potentiostaircase, and cyclic voltammetry, to analyze corrosion. These methodologies have the potential to yield substantial and valuable insights concerning the corrosion process's corrosion rate and the vulnerability of specific substances to corrosion in specified environments. Polarisation methods encompass the manipulation of the working electrode's potential and the subsequent observation of the resulting current in relation to time or potential. The cyclic polarization test was formerly used to assess the likelihood of pitting. During the test, the potential is varied in a single cycle, and the magnitude of the hysteresis is analyzed, along with the disparities between the values of the initial open circuit corrosion potential and the subsequent passivation potential [27-28]. Next is Cyclic voltammetry, which measures the current that develops throughout an electrochemical cell by spreading the potential measurement in a positive direction as long as an established amount of potential, or current, is reached, after which the scan is immediately turned towards a more significant negative until the initial amount of the potential is reached. The resulting current is measured [26].

The potential staircase method induces polarisation in an electrode by subjecting it to a sequence of potential steps, like a staircase. Each potential step is maintained for a fixed amount of time, during which the current is typically allowed to stabilize before transitioning to the next potential step. The critical distinction among these three polarisation methods is in their different approaches to calculating a potential current during corrosion measurements. In Cyclic Voltammetry, the potential is rapidly varied in only one cycle or even less. In contrast, in the Constant Potential Technique, the current is swept in the positive direction until a specific value is reached, and then it is swept back in the negative direction. During the afternoon, the potential sweep exhibits a pattern like a sequence of ascending and descending steps. Out of the three methods, the CV approach is the most suitable for quantifying the corrosion rate. Table 3 below summarized the comparison of corrosion measurement techniques.

Table 3 *Comparison of corrosion measurement techniques*

Measurement Technique	Description	Key Features	Limitations	Best Use Cases
Potentiodynamic Polarisation	Manipulates the working electrode's potential and observes the resulting current over time.	- Identifies corrosion rate and material vulnerability - Analyzes electrochemical behavior - Used for pitting corrosion analysis	- Requires controlled environment - Sensitive to electrode conditions	- Assessing material corrosion resistance - Pitting corrosion evaluation
Cyclic Voltammetry (CV)	Measures the current while sweeping the potential in a cycle, first in a positive direction and then reversing it.	- Rapidly varies potential - Captures oxidation-reduction reactions - Suitable for electrochemical reaction studies	- Limited to short-duration scans - Requires precise electrode preparation	- Studying redox behavior - Quantifying corrosion rate
Potential Staircase Method	Applies a series of discrete potential steps, holding each for a fixed duration before transitioning to the next.	- Stepwise approach stabilizes current at each level - Reduces noise in measurement - Useful for slow electrochemical reactions	- Slower than CV - Less effective for fast corrosion processes	- Measuring corrosion over extended timeframes - Stable electrochemical reactions

3. Methodology

The waterfall development process is being used for this project. The waterfall methodology approach involves dividing the whole software development process into distinct segments. Within the waterfall model, each phase must be fully completed before it can serve as the sequential input for the following step. The stages shown in Figure 1 are interconnected in a cascading manner, with progress seen as a continuous downward flow through each phase. The actions in each of the consecutive stages under the waterfall model process of development are summarised and clearly defined.

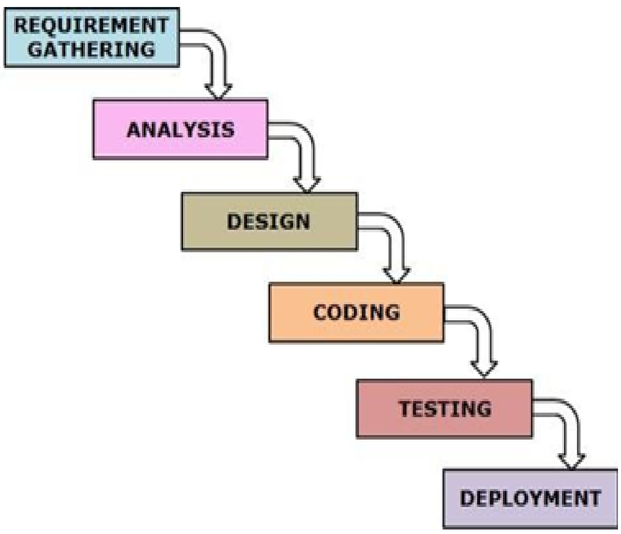

Fig. 1 *Waterfall model*

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In order to find relevant issue statements, a preliminary investigation is conducted during the requirement collection phase. The problem statements are used to provide a solution with suitable goals. To get a better grasp of why the expert needs to try the corrosion analysis method, an interview with a domain expert was also done. To further comprehend the typical needs of this project and to get a better picture of how corrosion analyses are carried out using conventional methods in the chemical science domain, background and related studies are also reviewed. System requirements are identified and defined during the analysis process. Project Scope, system capabilities, and limitations are defined with the input of the collected requirements. To help ensure a project's success, SWOT analyses are created. The next step in supporting the analysis process is to model a corresponding analysis diagram.

The system architecture is shown in the linked design diagram throughout the design process. The next step in designing the user interface of a mobile app is to sketch out the overall menu structure. Writing the actual source code for the Corrosion Analysis Tool in accordance with the design specification is done during the implementation phase. We make sure each function works by developing and testing it. After each unit is successfully implemented, it is added to the testing phase. The testing process involves integrating all of the created pieces into a system. The Corrosion Analysis Tool undergoes comprehensive integration testing to identify and fix any errors in its many functions. At this stage, we make any necessary improvements and adjustments to the Corrosion Analysis Tool. After that, testing is done to make sure the system meets the precise criteria. Finally, after the requirements have been met and all testing for the Corrosion Analysis Tool has been completed. At this point in the deployment process, the system is literally ready to go live.

Figure 2 shows the overall flow of how the system performs corrosion analysis and corrosion rate prediction. When the user wants to start the corrosion analysis process, the user first needs to have their experiment data file. The data file can be obtained by retrieving it from the microcontroller, and then it needs to be uploaded to the cloud storage. After the data file is uploaded, the user can access it and use it to start the corrosion analysis process. First, the system will pre-process the data file by organizing the data in the proper structure and format. Then, the system will start to calculate and form a standard formula for calculating the sample concentration using a linear regression algorithm. After the formula is formed, the system will identify the anodic peak current from the unknown sample data file. Then, the anodic peak current will be added to the standard formula to calculate the concentration of the unknown sample. After that, the concentration of the unknown samples and other data inputs such as immersion time, the density of the metal, area, and volume will be placed in the corrosion rate format formula to calculate the corrosion rate. Finally, the result will be displayed to the user in the dashboard. Before saving the record, the user is able to decide whether to predict the corrosion rate or not. If yes, the user will need to submit the duration of immersion time they want to predict. Then, the system will use the immersion time as a parameter to indicate the anodic peak current for the unknown sample using the random forest regression algorithm. Once the anodic peak current is predicted, use the previously outlined steps to calculate the expected corrosion rate. Afterward, the user can save the analysis record for future reference.

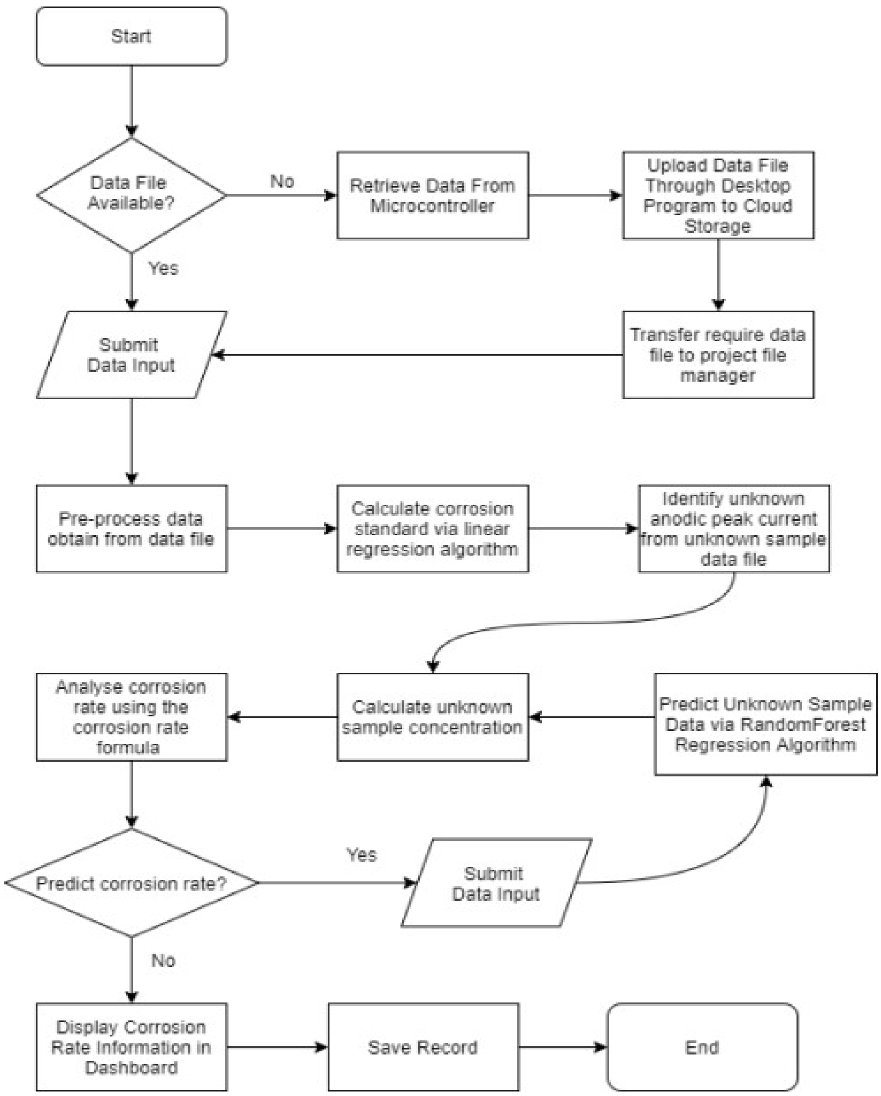

Fig. 2 *Flowchart of corrosion analysis*

4. Implementation

Figure 3 shows system architecture diagram for the Corrosion Analysis Tool. The potentiostat microcontroller is used to collect data from the graphite pencil electrode sensor. The data is then uploaded to the cloud services for data analysis via the desktop application. Since the microcontroller does not include Wi-Fi and Bluetooth features, the only way to transfer data is through a desktop application and upload it to the cloud storage; then, it can be processed with the mobile application. Hence, the mobile application is capable of retrieving data from two inputs, which are from the data that is available in the cloud storage, and the user may upload their dataset from their smartphone's local folder directly. The user will use the mobile application to control the system flow. A cloud database will be used to store data after it has been uploaded to the cloud. If any function is triggered from the mobile application, the app will send a request to the cloud server to initiate a response using the cloud function service. After the response is returned to the app, the user may provide action on the responses, such as performing a corrosion study with the analyzed data that is returned from the cloud function service.

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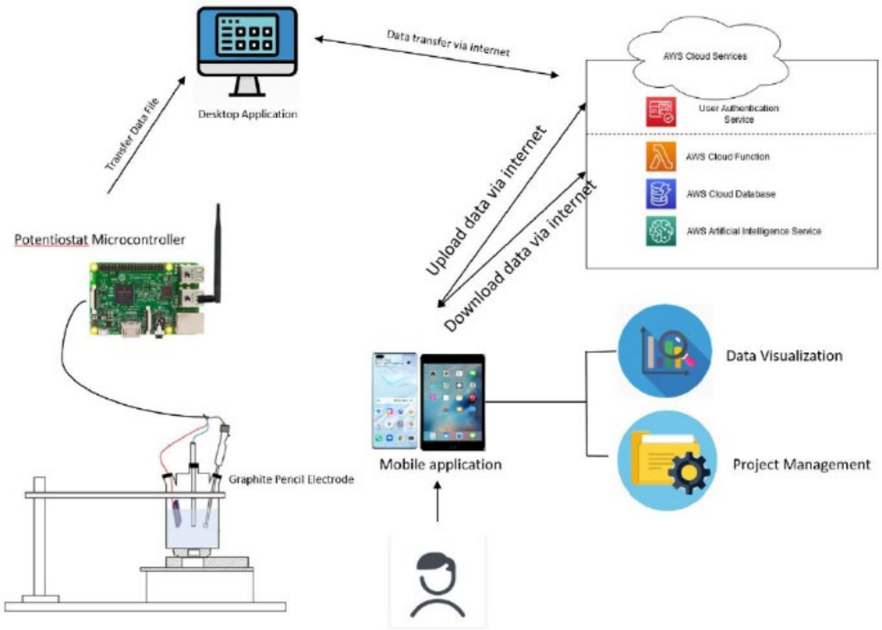


Fig. 3 *System architecture of corrosion analysis tool*

4.1 System Modules

System modules are discrete building blocks of a more extensive system with the purpose of performing a single function. It is a blueprint for the system at a high level that shows how all the pieces interact with one another. The smartphone app, microcontroller, and back-end services modules are the major components of this project.

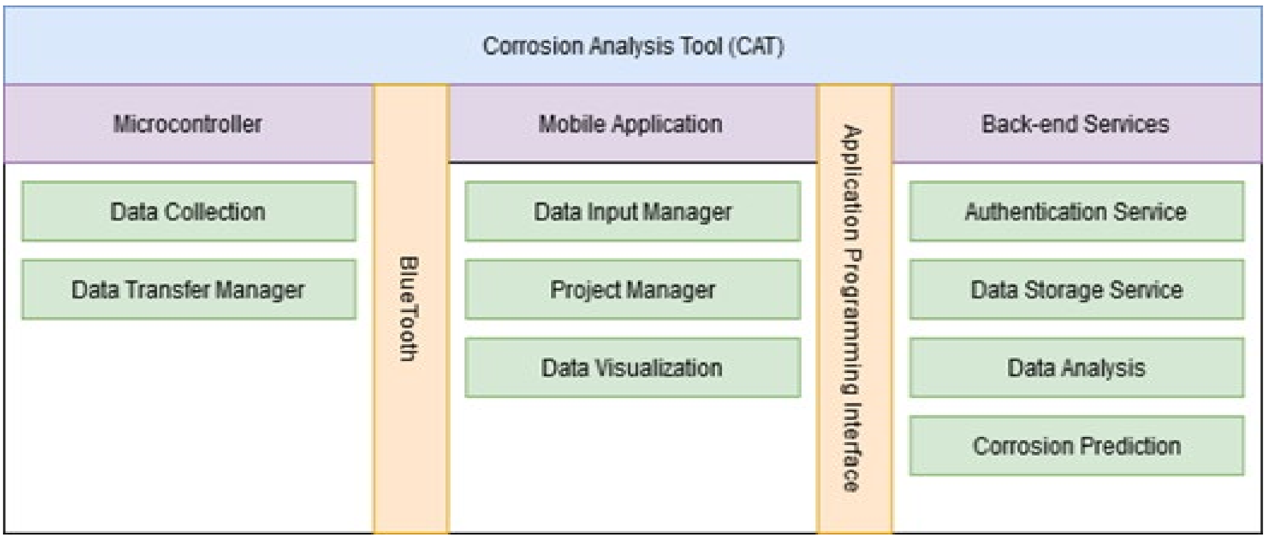


Fig. 4 *System module diagram*

4.1.1 Microcontroller Module

This module will handle the potentiostat microcontroller. The module will handle the data collection received from the pencil graphic electrode sensor. The data transfer manager will handle the transfer mechanism between the microcontroller and the mobile application via Wi-Fi with the help of a desktop application. The reason for using the desktop application is that the microcontroller does not include Wi-Fi or Bluetooth features, and the data extracted from the microcontroller needs the help of Wheestat software.

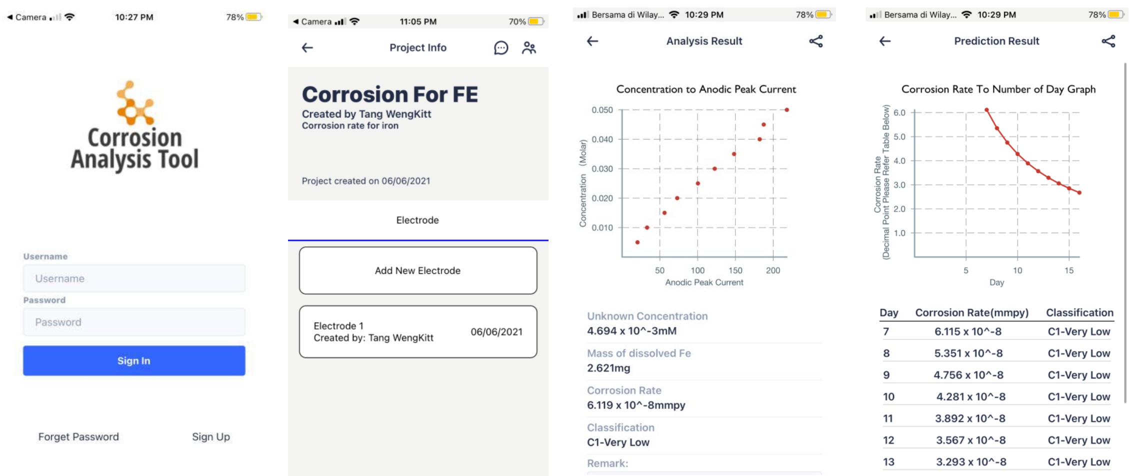
4.1.2 Mobile Application Module

The mobile application module will be the main module for this system. Most of the front-end system flow will be coordinated in this module. This module allows the user to manage projects, and the user is capable of creating, removing, or viewing a project. The user is also capable of searching for their project with the project manager. After a user does a project, the user will need to input data to start the analysis process. The microcontroller manager will come in to help retrieve the data from the microcontroller, and only then will the data be uploaded to the cloud for further analysis. After the data is processed and analyzed, the analyzed data will return as the result of the corrosion analysis experiment. Users can perform data monitoring, data analysis study, and experiment logging to make notes for specific project experiments.

4.1.3 Back-end Services Module

The back-end service module will be the core module of the Corrosion Analysis Tool system because most of the logic functions will be processed by this module. The cloud services provide functions such as authentication, data storage, machine learning and back-end function run time. Authentication will help in managing the system user pool, which allows users to register and log in to the system. On the other hand, the data storage service will be handling all in and out data from the cloud storage. There will be two types of cloud storage used in this system. The first one is the S3 bucket that is used to store user raw analytic data, and the other one is DynamoDB, which is used to store info for the user, project, and result from the corrosion analysis. Another reason that the S3 bucket will be used is to use it as a data storage or input for the machine learning function to build and deploy the model. After the machine learning model is built, it will be deployed to the S3 bucket to allow the back-end function to make prediction queries.

4.2 System UI



(a) (b) (c) (d)

Fig. 5 *System user interface (a) Login page; (b) Project info dashboard; (c) Corrosion rate result screen; and (d) Prediction corrosion rate result screen*

5. Evaluation

The results produced by the system are verified by comparing the results obtained from the actual experiment in the lab done by students at the School of Chemical Sciences, USM. The result of this study is computed manually using the traditional method by the students. Table 4 shows the comparison of the accuracy results calculated by the system and obtained from the actual experiment.

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Table 4 *Result of corrosion rate analysis accuracy test*

Experiment immersion time (Day)	Corrosion rate result from actual experiment	Corrosion rate result from Corrosion Analysis Tool	Result Different
7	5.476x10^-8	5.240x10^-8	0.236
14	2.812x10^-8	2.763x10^-8	0.049
21	1.913x10^-8	1.842x10^-8	0.071
28	1.753x10^-8	1.739x10^-8	0.014

The result produced by the system is similar compared with the result obtained from the laboratory experiment. Hence, the system's result is acceptable. Thus, the corrosion analysis tool passed the precision test. It is clear from the data that the system satisfies the criteria laid forth in the report's analysis part. First, for the project management requirement, the application is able to manage the project and experiment record well. All the documents can be easily found through the search function, and they are stored correctly by the user. No mismatch error is found. Next, for the data file management function, all the data files uploaded by the user from the file uploader desktop program or mobile local storage are successfully uploaded to the database and accessible by the user from the mobile application to perform corrosion rate analysis submission. After the user creates a new project, the user is able to understand the purpose of the project through the project description in the project dashboard. Then, the user is also able to manage the project group members and communicate with them through the real-time messaging function in the project dashboard. In the dashboard, the user is able to create an electrode to start adding analysis records. In terms of the analysis process, the system is able to return the corrosion rate result to the user after the user submits the analysis form. From the results of the analysis, the system is also able to help users predict the corrosion rate for future preparation. Lastly, the system is able to re-analyze the corrosion rate with other unknown sample data points. However, there is a limitation when it comes to file input format to the system. The file format needs to be a simple text file in the Txt extension, and the structure of the content in the file needs to follow the format generated from the potentiostat. Hence, the system does not accept files with another format.

6. Conclusions

In conclusion, the Corrosion Analysis Tool system has been successfully developed based on the proposed solution, which is expected to provide mobility and automate the corrosion analysis process for chemistry researchers. The results have met all the user's requirements to help them complete their corrosion analysis experiment more quickly and conveniently. This system will help reduce human calculation errors or systematic errors, such as reading the value using the traditional way, because currently, the user is performing the corrosion analysis process manually, and it isn't very easy for the user. The corrosion Analysis Tool system has also been developed with a project management feature, which will help the user manage their project correctly. From the historical method, the user keeps their project folder or information in computer storage or on the drawer shelf. The project folder is not centralized even with the help of storing in computer storage because it will cause the user to find the folder here and there, or sometimes the project may need to be completed, missing or contain a data redundancy problem. Hence, with the help of the Corrosion Analysis Tool system, the user is capable of managing their project in a better way to prevent any information loss disaster. Lastly, the Corrosion Analysis Tool system achieved a significant milestone by incorporating artificial intelligence into the field of chemical science. In this project, machine learning will be utilized as the AI algorithm. By using machine learning, the Corrosion Analysis Tool system is expected to provide a user data prediction feature that will give them an excellent opportunity to conduct a further investigation on their corrosion experiment. The predicted result will help the researcher to understand the status of the target analyte more clearly and prepare to stabilize the target if anything happens in the future.

Conflict of Interest

Authors declare that there is no conflict of interest regarding the publication of the paper.

Author Contribution

The authors confirm contribution to the paper as follows: ***study conception design:*** *Siti Hazyanti, Tang Weng Kitt;* ***data collection:*** *Tang Weng Kitt;* ***analysis and interpretation of result:*** *Mohd Azam, Mohd Hazwan;* ***draft manuscript preparation:*** *Siti Hazyanti.*

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