



MOSS: AI Platform for Discovery of Corrosion-Resistant Materials

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ABSTRACT

Amid corrosion degradation of metallic structures causing expenses nearing \$3 trillion or 4% of the GDP annually along with major safety risks, the adoption of AI technologies for accelerating the materials science life-cycle for developing materials with better corrosive properties is paramount. While initial machine learning models for corrosion assessment are being proposed in the literature, their incorporation into end-to-end tools for field experimentation by corrosion scientists remains largely unexplored. To fill this void, our university data science team in collaboration with the materials science unit at the Army Research Lab have jointly developed MOSS, an innovative AI-based digital platform to support material science corrosion research. MOSS features user-friendly iPadOS app for in-field corrosion progression data collection, deep-learning corrosion assessor, robust data repository system for long-term experimental data modeling, and visual analytics web portal for material science research. In this demonstration, we showcase the key innovations of the MOSS platform via use cases supporting the corrosion exploration processes, with the promise of accelerating the discovery of new materials. We open a MOSS video demo at: <https://www.youtube.com/watch?v=CzcxMMRsxkE>

CCS CONCEPTS

• Human-centered computing → Ubiquitous and mobile computing systems and tools; • Applied computing → Physical sciences and engineering.

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KEYWORDS

Corrosion Science; Automatic Assessment; Deep Learning

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1 INTRODUCTION

Motivation. Corrosion represents a world-wide problem, costing the global economy nearly \$3 trillion annually equivalent to approximately 4% of global GDP [2, 9]. It also raises significant safety concerns, as corrosion can severely degrade the structural integrity of metallic infrastructures, posing threats to human lives and the environment. The development of materials with superior corrosion resistance properties has thus been recognized as a critical research area in the materials science community [1, 4, 5, 10, 15, 18, 19, 23].

State-of-Art. Historically, the development of corrosion-resistant materials has relied on time-consuming manual procedures and experiments [22]. This traditional approach is plagued by inefficiencies and worse yet, human error. To overcome this, radical changes in corrosion assessment processes are needed. The recent advances in artificial intelligence (AI) promise to innovate the materials science life-cycle to streamline processes and improve results. As first steps into this direction, machine learning models for corrosion assessment began to be explored in the academic literature [3, 11, 17, 21, 22]. However, the integration of these AI models into comprehensive end-to-end tools to support in-field experimentation by material scientists remains largely unexplored.

Our Approach. In this work, we respond to this critical need by introducing MOSS, an innovative AI-based digital platform designed to support corrosion research and assessment. This initiative

is the result of a collaboration between the data science team at WPI and the materials science unit at the Army Research Lab. Our MOSS platform encompasses a suite of user-centric services aimed at supporting the corrosion research process. One, this includes an intuitive iPadOS app for reliable and efficient collection of corrosion progression data in the field by capturing images of treated materials and auto-linking them to prior instances over time. Two, this tool incorporates deep-learning modules for supporting effective analytics, including the rapid assessment of corrosion of these recorded experimental materials. Three, the MOSS features a robust data repository for storage and modeling of the collected experimental data characterized by rich metadata and properties, such as geo-location, time, materials, and more. Four, the visual analytics web portal provides advanced services to support material scientists in their exploration of their experimental data – supporting corrosion exploration processes such as pattern recognition and corrosion rating classification.

In this demonstration, we showcase through real-world use cases how MOSS supports and expedites corrosion assessments over time and with it the development of new corrosion-resistant materials. This ultimately may contribute to the reduction of the economic burden and safety problems caused by corrosion of our national infrastructure. Our vision is to inspire a broader adoption of AI technologies in corrosion research in particular and, in doing so, ignite a revolution in the field of materials sciences in general. Our MOSS platform has been deployed and attempted at the Army Research Lab. We provide a video demo at: <https://www.youtube.com/watch?v=CzcMMRsxkE>

2 BACKGROUND AND MOSS SYSTEM

2.1 Background on Corrosion Assessment

Figure 1 depicts manufacturing processes of the material products under testing, the testing procedures, and labeling procedure. The materials are composed using a layered stack up consisting of a topcoat, primer, pretreatment, surface profile, and substrate layer onto panels for corrosion assessment. The five constituent layers of the coating stack up for each sample are reinforced by multiple replicates of the same stack up to provide an adequate statistical sample for material performance testing. Corrosion experiments are conducted by domain scientists in two main scenarios: indoor laboratory-based tests and outdoor natural environment tests. The



Figure 1: Standard Corrosion Science Experiment: Each material is manufactured into sample panels (Left Top). They are assessed (Left Bottom) after being exposed to indoor (Right) or outdoor (Middle) environments.

indoor tests are used as quality control and speed-up of sample production to reduce the labor investment needed for outdoor tests. Outdoor corrosion tests consist of placing panels directly into their natural target environments, such as, humid sites in Florida or hot sites in Arizona. Corrosion technicians evaluate the anti-corrosive performance of material sample panels according to material science standards and record them in notebooks or Excel tables [22]. In order to improve the quality, reliability, and utility of these long-term testing performance data, an end-to-end platform should be designed and developed to unify data collection, management, analysis, assessment automation, and further research for the discovery of corrosion-resistant materials.

2.2 MOSS Platform and Its Components

The architecture of the MOSS platform is depicted in Figure 2. MOSS is composed of a set of interconnected components that each play a crucial role in enhancing the efficiency, accuracy, and scope of corrosion studies. These components encompass an intuitive iPadOS app for scientific data collection over time, a deep-learning module for tasks such as automatic corrosion assessment, a visual analytics web portal for corrosion research, and a unified backend for long-term storage and modeling of experimental data serving the app and web. Altogether, MOSS charged with the power of AI supports an efficient material discovery process.

3 MOSS CAPABILITIES AND INNOVATIONS

3.1 Mobile App for Data Collection

In response to the limitations of traditional manual data collection for corrosion progression data, we introduced a more efficient solution – an iPad app designed for MOSS data collection. The primary aim of the app is to enable the systematic and consistent capture of corrosion images over time, thereby minimizing human error and increasing efficiency in data acquisition across diverse experimental conditions (time and locations) and technicians. The MOSS platform incorporates a QR code system to track and manage corrosion samples (See Sec. 3.3). Researchers can easily scan the QR code in the field using an iPad app to access and update sample data.

The app also allows for real-time annotation and documentation of image metadata, ensuring accurate and comprehensive data records that can be taken while on the field, yet is seamlessly integrated with the digital experimental repository. Considering the potential connectivity issues in remote field locations, the app functions robustly under low WiFi conditions, saving data locally first, then executing a delayed secure upload to the server once WiFi is available. This ensures that the data collection to the backend server is not compromised, regardless of field conditions.

3.2 MOSS Deep-Learning Models

The heart of MOSS is its distinctively engineered deep learning models for automating corrosion assessment and generation (See Figure 2). For classifying corrosion, it incorporates models like HRNet [24], ResNet [20], MAE [6], PIRL [16]. In terms of generation, the platform leverages cGAN [14] to create future corrosion images. To bridge the gap between indoor and outdoor corrosion ratings, MOSS utilizes domain adaptation techniques such as CDAN [12], JAN [13], MCC [7]. For material scientists to gain trust in the

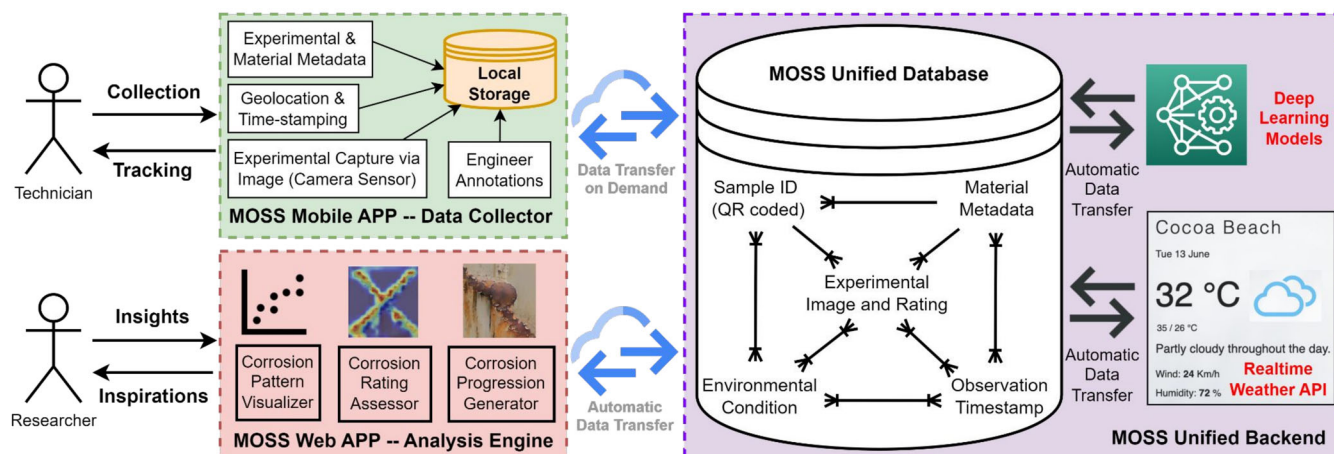


Figure 2: MOSS Platform to Support Material Discovery

technology, we also incorporate Explainable Artificial Intelligence (XAI) into our deep-learning models. This includes prediction confidence based on softmax outputs and Grad-CAM results, which highlight the image areas most utilized by the model. Illustrated by Figure 2's "Corrosion Rating Assessor", these insights can spark new research hypotheses and aid the development of more durable, corrosion-resistant materials.

As demonstrated in Figure 5, MOSS is capable of rating each material sample based on a given image into 1 of 10 classes of corrosion severity levels, where the class indicates the level of corrosion from none to extremely severe. These embedded models have been trained on a diverse dataset of corrosion images which we curated and released to the community [8, 22]. Importantly, they are designed for quick response, providing the corrosion prediction results within less than 2 seconds per request. In addition, the models are integrated into the MOSS unified repository via plug-ins. This tactical arrangement eases the process of adding new models or updating existing ones, thereby ensuring the MOSS platform remains at the cutting edge of corrosion research and technology.

3.3 MOSS Unified Repository

MOSS includes a robust data repository system for the storage and modeling of experimental data with user authentication. This system is built to securely house experimental data, allowing for long-term studies and the building of comprehensive corrosion models. It interacts with the MOSS mobile app, capturing and processing data that is then enriched with domain-specific entity relations for a more insightful analysis. The system is also integrated with a real-time weather API that automatically fetches weather information based on assessed timestamps and geolocation (See Figure 2).

The system features a range of data management tools, including data versioning, metadata management, and advanced search capabilities. This allows researchers to easily locate data from past experiments, enhancing the efficiency of their research and enabling the creation of increasingly accurate and detailed models of corrosion progression. It also implements a QR code system for tracking corrosion samples, with key records updated via MOSS mobile app in the field such as collection date and location, thereby ensuring

accurate results attribution in the lab and improving experimental management, collaboration, and data integrity. To further enhance its utility, it incorporates deep learning models capable of automatically evaluating and creating images relevant to corrosion. All of these features are accessible via the MOSS web portal. This system enables interactive data analysis and deep learning predictions (See Figure 2), making MOSS an invaluable tool for researchers.

3.4 MOSS Analytics Web Portal

The MOSS platform encapsulates an innovative data analysis web portal, providing a sophisticated toolset for supporting the research and analysis of material discovery. It engines visual exploration, interactive analysis, automatic corrosion assessment, and the generation of actionable insights underpinned by advanced deep-learning methodologies. Connecting with the MOSS unified data repository backend, this portal not only empowers the researchers to make data-driven decisions but also facilitates collaboration with field technicians in designing effective experiments.

Merging advanced technology into this intuitive interface, the portal streamlines the research process, offering a new paradigm in how scientists engage with and manage corrosion studies (See Figure 2). The "Corrosion Pattern Visualizer" enables intuitive interpretation of data by allowing researchers to visually analyze and identify key corrosion patterns and trends, thus enhancing decision-making in corrosion studies. The "Corrosion Rating Assessor" leverages deep learning and XAI models to provide interpretable assessments of corrosion severity. This, as seen in Figure 2 and Figure 5, ensures results are accessible and fosters a deep connection between material scientists and AI models. Lastly, the "Corrosion Progression Generator" employs generative AI models to simulate the future progression of corrosion, encouraging a predictive understanding of corrosion patterns and fostering collaboration between researchers and AI tools, which ultimately contributes to the discovery of corrosion-resistant materials.

4 DEMONSTRATION

The MOSS platform, in a real-world setting, is utilized in field studies to analyze corrosion progression in different materials. The

accompanying app facilitates comprehensive real-time data collection, including photos, material condition notes, and environmental readings, even under limited internet connectivity. Once data is collected, it is uploaded for analysis on the server and web portal. The platform's deep-learning module assesses each material sample's corrosion state, providing clear and automatic insights into corrosion understanding.

iPadOS App to Serve Data Collection. Initial data collection is carried out using the user-friendly iPadOS app. A technician can collect, annotate, and save their experimental procedures and observations in an organized fashion. After logging in, the technician can begin to review or create new experiment sessions and tasks. Users can review past experiments and detailed records. Each material sample, complete with its details such as surface substrate, pretreatment, profile, primer, topcoat, timestamp, and a unique QR code, can be reviewed and shared among a team.

As seen in Figure 3, a new experiment can be created, wherein a user can photograph the material and input corrosion measurements. Corresponding rating scores are then calculated and displayed in boxes, with our deep learning algorithm offering a predicted corrosion rating for optional inclusion.

Data Repository to enable long-term data integration. After collecting data for an experiment session, the user can select and back the data up to the data repository. This data repository allows for long-term and comparative studies, assisting in building a comprehensive understanding of corrosion progression. The system's advanced search capabilities, along with data versioning features, ensure efficient data management and uphold data integrity.

Figure 3: Capture, record, and save all experimental information about a new experiment.

Web portal to enable Deep Learning and Visual Analysis. After collecting and saving data, further analysis and discoveries can be done through our web portal. As seen in Figure 4, the web portal allows for interactive data visualization from MOSS unified database to recognize patterns and interrelationships of detailed corrosion ratings on samples, weather conditions, and materials.

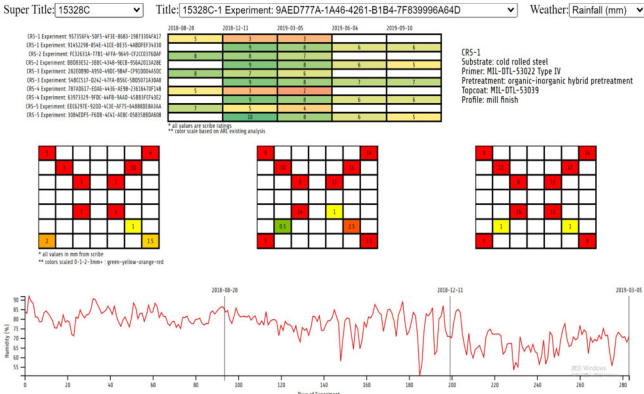


Figure 4: Select from a variety of plotting tools and material features to visualize trends and relationships across observations of corrosion progression ratings.

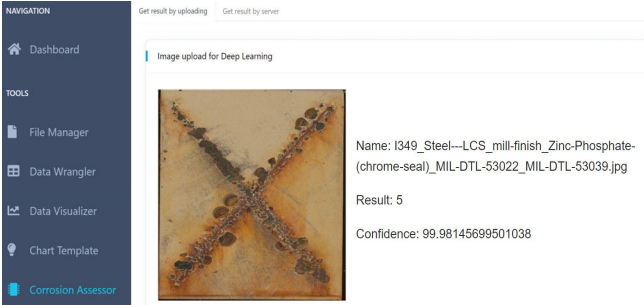


Figure 5: Automatically assess a corrosion panel image with embedded deep learning classification model. Confidence shows the softmax probability of the predicted class.

Most importantly, corrosion and AI researchers can easily access the data and view manual and automatic assessments by interacting with the embedded deep-learning models. Sample image results from the database can be displayed on the web portal (See "Get results by server" tab in Figure 5), where researchers can also upload local images to view deep-learning results (See "Get results by uploading" tab and results shown in Figure 5)

5 CONCLUSION

This demonstration showcases our MOSS platform that supports the discovery of metallic materials with superior corrosion-resistant properties – promising to improve global safety.

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