Democratizing Deep Learning Applications in Earth and Climate Sciences on the Web: EarthAIHub

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Abstract
Most deep learning application studies have limited accessibility and reproducibility for researchers and students in many domains, especially in earth and climate sciences. In order to provide a step towards improving accessibility to deep learning models in such disciplines, this study presents a community-driven framework and repository, EarthAIHub, that is powered by TensorFlow.js, where deep learning models can be tested and run without extensive technical knowledge. In order to achieve this, we present a configuration data specification to form a middleware, an abstraction layer, between the framework and deep learning models. Once an easy-to-create configuration file is generated for a model by the user, EarthAIHub seamlessly makes the model publicly available for testing and access using a web platform. The platform and community-enabled model repository will benefit students and researchers who are new to the deep learning domain by enabling them to access and test existing models in the community with their datasets, and researchers to share their novel deep learning models with the community. The platform will help researchers test models before adapting them to their research and learn about the model details and performance.

1. Introduction

One of the main issues regarding applicable deep learning research is the availability of the models, case studies, and research in an easy and accessible way to other researchers (Sit et al., 2020). While reproducing results has been possible, albeit both time and resource-intensive, for experts in the field, it remains a problem for non-technical people, researchers, and students who are new to this domain to see how well a deep learning model performs over their own inputs. This is mostly due to either computational limitations or allocating the time needed for setting up and testing many models they might consider for their research. Many studies (Isola et al., 2017; Karras et al., 2019) make an extra effort to support scientific communication and reproducibility by providing a working example of their study in a web-friendly format that, more often than not, accepts inputs from users and returns an output. Such applications typically carry some popular science and outreach value. Another approach used by deep learning researchers to communicate their findings to the public is to provide their code and trained deep learning models via platforms such as GitHub and various deep learning model repositories, often called model zoos (i.e., ONNX Model Zoo, Nvidia's NGC Catalog).

While most studies adopt the latter way to enable other people to try their research, this tendency has a logistically sound reason. Even though it is vital for the audience to be able to see how the findings of some research are realized in real-world settings, it is also difficult to provide an end-product that employs the presented research for third parties to use. Providing proof of concept for the research is the backbone for any study to be useful and accessible to others. It is also resource-consuming for researchers to transform that proof of concept into a working application for real-world use cases most of the time. The resource-wise needs for an application typically comprise many things, from labor to computational power. From a researcher's perspective, it is more sensible to utilize those resources in further research instead of allocating them for a real-world application just for some publicity. One could argue that computational power needs could be surpassed by just implementing a web application that utilizes the client side's computational power. This would be a reasonable approach in order to get past the problem of devoting costly computational capabilities, but it also adds to the need for labor since, typically, a deep learning model is developed in an experimental setting in server-side programming languages such as Python. Consequently, researchers typically prefer to release the code that could be used to reproduce the results, sometimes alongside a pre-trained model. This, in theory, is an attempt to communicate the study's findings, but by its nature, it only communicates with other researchers, who are willing to put the necessary time in to advance the science rather than supporting non-technical people who might be interested in, and beyond that, could benefit from, the conducted research.

Most of the time, these studies share their model code on platforms like GitHub, linking their pre-trained models stored in the cloud. Beyond that, there are many "model zoos" from which many pre-trained state-of-the-art models for common tasks could be acquired. These zoos occasionally include the code and sometimes give out instructions to show how to utilize the given model. While there are examples of model zoos that are framework-blind, in other words, model zoos that do not have specific framework requirements, such as modelzoo.co (Model Zoo, 2021), most numeric computing libraries also have their own zoos in their repositories, such as TensorFlow (Abadi et al., 2015) and Open Neural Network Exchange (ONNX, 2021). While the ones mentioned were community-driven efforts, there are some model zoos that list ready-to-use deep learning models in specific commercial AI devices, such as Texas Instruments' TI Edge AI Cloud (Texas Instruments, 2021) and Hailo.ai's Model Zoo (Hailo AI, 2021). Besides all these examples, Nvidia's NGC Catalog (Nvidia, 2021) also provides many state-of-the-art models with instructions on how to run them on containers.

Besides aforementioned model zoos, a rare minority of studies in the literature choose to provide a working application, most of the time in the form of a web application. This has been mainly for generative works, as these models typically expect minimal input from the user. Thus, they are easier to conceptualize on the web, though, most of the time, not by the original authors. Such examples have primarily been in the "this *thing* does not exist" format. They typically show a completely new output generated by the proposed network at each reload of the web application. The list of studies employing this approach includes but is not limited to face generation (This Person Does Not Exist, 2021; Karras et al., 2019), vase image generation (This vessel does not exist, 2021), resume generation (This resume does not exist, 2021) and artwork generation (This artwork does not exist, 2021). Beyond these, there are some of the ONNX models from the ONNX zoo that are presented at the ONNX.js (Microsoft, 2021) demo website, such as emotion detection (Barsoum et al., 2016) and object detection (Redmon and Farhadi, 2017).

There are also other practical applications of deep learning models available on the web, such as Quick Draw by Google that predicts what a user is drawing (Google, 2021), and pix2pix (Isola et al., 2017) that converts your drawing to a photo (Affine Layer, 2021). Online deployments of language models such as GPT-3 (Brown et al., 2020) could also be mentioned as examples of deep learning models running on browsers. It should be noted that, even though some of the studies mentioned here use server-side resources, they typically utilize client-side resources. One commonality among these models is that they depend on individual efforts to communicate their findings. Aside from the ONNX.js showcase, which is only for demonstrating purposes, they do not share a common platform or methodology to include non-technical people in AI research or other domains.

In order to understand how deep learning models could be run on the web, specifically on the client-side, it is of utmost importance to discuss how client-side computing is done. Conventionally, computing on the web has been primarily for citizen science purposes. From extraterrestrial research (Anderson et al., 2002) to hydroscience (Agliamzanov et al., 2019), there are many studies in the literature that take advantage of the client-side resources of volunteers to advance science, some of which are on browsers. With deep learning being a part of many applicable studies, ways to utilize computing on browsers are explored for deep neural networks as well. Literature on client-side tensor computing libraries, in other words, deep learning frameworks that work on browsers, is abundant. ONNX.js, Keras.js (Chen, 2021), and TensorFlow.js (Smilkov et al., 2019) are popular libraries used in many studies.

Open Neural Network Exchange, or ONNX, is an attempt that aims to be a middleware between many tensor computing libraries such as TensorFlow, PyTorch (Paszke et al., 2019), and MXNet (Chen et al., 2015). ONNX provides programmable interfaces to convert models between popular tensor computing libraries. Even though ONNX has its own runtime as a Python package to run converted models, one could also convert an ONNX model to another framework's model format. Beyond Python, the ONNX ecosystem provides a package to run ONNX models on browsers called ONNX.js. ONNX.js, though with limitations in terms of implemented architectures, provides a medium to run ONNX models in browsers. For performance purposes, the ONNX.js runtime supports web technologies like WebAssembly and WebGL. One drawback ONNX and inherently ONNX.js carry might be that one cannot train a model using them. Considering they do not aim to provide training functionality in the first place, that would be an arguable drawback. It should be noted that ONNX.js was replaced by ONNX Runtime Web (Microsoft, 2021), which also works in JavaScript. Since it is still in active development, it does not provide a viable framework to build a generalized deep learning platform.

One popular deep learning package for JavaScript and browsers is Keras.js. Using the boilerplate of a popular deep learning package, Keras (Keras Team, 2021), Keras.js provides an easy-to-use framework to train and run deep learning models. While it was one of the go-to solutions to deploy some deep learning models on the web when it was first released, it is not actively maintained as of now in favor of TensorFlow.js. TensorFlow.js uses the TensorFlow library, which is backed by Google. Now that Keras models and TensorFlow models are somewhat intertwined, TensorFlow.js supports both Keras and TensorFlow models, which covers a great majority of deep learning models but not as much of the applicable research. Beyond that, TensorFlow.js has the most functionality that Keras and TensorFlow provide in terms of available architectures and matrix operations. This makes TensorFlow.js the most popular deep learning framework for online applications. Similar to ONNX.js, TensorFlow.js also supports WebAssembly and WebGL for faster training and execution.

Furthermore, there are a few other deep learning frameworks that run on JavaScript and subsequently could be used on web browsers, such as WebDNN (Machine Intelligence Laboratory, 2021), ConvNet.js (Karpathy, 2021) and brain.js (BrainJS, 2021), but they don't focus on the community support and practicality like TensorFlow.js. One exception might be ml5.js (ml5, 2021) which runs on TensorFlow.js and aims to provide an abstraction layer to make running models on the web more accessible, thus differentiating itself from others in terms of audience and value. There are vast quantities of deep learning application papers published every day. Most of the time, the research is not easily reproducible. Even when the code or pre-trained models are provided, since all deep learning frameworks need some level of expertise to run a model, people with no AI modeling experience will not be able to run and see the results of a study for themselves.

Deep learning has been a methodology of interest for many earth science studies. Whether it be about social media streams, like Twitter data, that is related to natural disasters (Sit et al., 2019), or digital elevation models (Demiray et al., 2021b), there are many studies in the earth science that utilize deep learning methods. Modeling floods for prediction (Sit et al., 2021a; Xiang et al., 2021) and rainfall to increase the temporal interpolation (Sit et al., 2021b) are among deep learning applications studies in the field along with benchmark dataset efforts (Ebert-Uphoff et al., 2017) to support the literature (Sit et al., 2021c; Demir et al., 2021). Even though deep learning application studies are somewhat in abundance in the earth and climate sciences literature, there are still challenges in scientific communication of studies utilizing deep learning. To the best of our knowledge, there are not any studies that share their developed and trained deep learning models for earth and climate sciences problems on the web for third parties to experience. Beyond already published studies, similar to any data driven methodology, adopting deep learning in their applications is appealing to domain scientists, i.e., scientists who are experts in earth and climate sciences but might not have the technical expertise to apply deep learning in their field. In order for them to start exploring how deep learning could be utilized in their fields, understanding the literature beyond what scientific literature presents is of utmost importance to capitalize the deep learning based modelling potential in the field.

This study aims to empower domain scientists from earth and climate sciences to reproduce and test previously trained deep learning models easily with their data and settings without having to train or even know how to use a specific tensor computation library used in selected projects. We present EarthAIHub, an easy-to-use web application utilizing client-side resources to run deep learning applications. The EarthAIHub is designed with a community-centered approach and easy-to-use model configuration templates to deploy models to the platform for others to test and experience for the long-term sustainability of the user base.

The rest of this paper is structured as follows; in the next section, we detail the implementation of the web application to explain how deep learning models specified for different tasks could run on the same platform. Then, in section 3, we present selected deep learning models in environmental science and show how configurations could be built for them and run on EarthAIHub. Finally, in section 4, we discuss our findings and share final remarks.

2. Methodology

In this section, we describe the architecture and implementation details of the application on the server-side and the client-side, and present the model specification and process to deploy a model at the platform.

2.1. Architecture and Modules

EarthAIHub (Figure 1) is a web-based deep learning hub (https://earthaihub.org) for earth and climate researchers for accessing and running pre-trained DL models. While data management and user authentication are done on the server-side, the most crucial task, running models, is done at the client-side. This allows minimizing the computational dependency on the server-side, reduce the cost, and improve sustainability of the platform. In order to do so, we implement a RESTful API and a client-side single-page web application that communicates with the API. Embedded into the client-side web application, a JavaScript Web Worker facilitates the running of models using TensorFlow.js without interrupting the interface and user interactions.

The EarthAIHub runs on stack based on Flask, which is a web framework in Python. We use TensorFlow.js for running pre-trained models on the client-side, and Flask-RESTful, a Flask package that extends Flask's capabilities to implement RESTful services easily on the server-side. Vue.js, a client-side JavaScript library is used to build single-page interfaces, and Bulma, a CSS framework that has modern-looking HTML elements is used for the design. In order to avoid extra workload, we chose to use SQLite as the database and the Flask-SQLAlchemy package to ensure communication between the database and Flask. To facilitate the core functionality, the platform is built upon four modules that interacts independently with the database and other modules, namely, the User Management Module, Model Management Module, Administration Module, and Compute Module (Figure 2). Aside from these modules, there are also detailed documentation pages that EarthAIHub presents for referencing purposes.

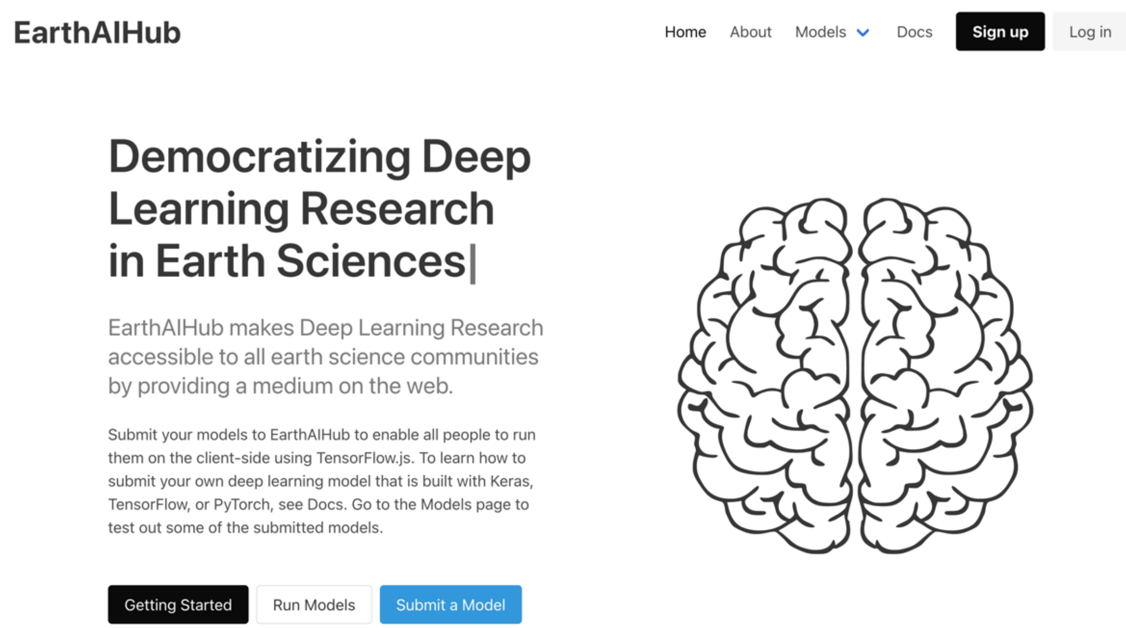

Figure 1. Homepage of EarthAIHub

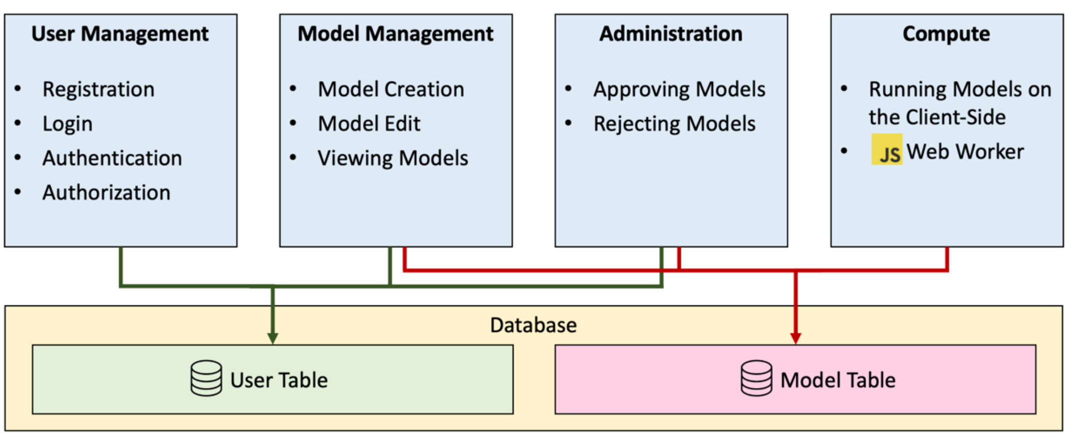

Figure 2. Modules and their connections over different tasks on EarthAIHub

2.2. Model Specification

EarthAIHub accepts TensorFlow.js GraphDef model format, also known as SavedModel, that could be read with *tf.loadGraphModel(...)* function. As this function expects the path to the *model.json* file and that file is typically accompanied by several binary files, all of which are needed by the platform for proper execution. In order to ensure that, the web app expects a zip archive of all binary files and the *model.json* file in which the *model.json* is stored at the root of the zip archive at submission time. An example zip archive includes the model configuration file (i.e., model.json), and several binary files (i.e., group1-shard1of3.bin, group1-shard2of3.bin, group1-shard1of2.bin).

EarthAIHub is designed to support two types of users namely model developers and model users from earth and climate science domain. Consequently, the main task for the platform is to provide abstraction layers. In order to do so, we designed a configuration file format and specification that defines all the things user would need to run a TensorFlow.js model. The configuration file includes input format, output format, preprocessing type, preprocessing function, postprocessing type, and postprocessing function. Fields and their definitions for the config file can be seen in Tables A1-A5 in the Appendix. An example model configuration file can be seen in Figure 3.

```json
{
  "name": "mnist",
  "input": "img",
  "output": "raw",
  "preprocess": "func/tensor-tensor",
  "preprocessFunction": "function preprocess(res) {res=tf
    .gather(res, [0], axis=1).mul(0.3).add(tf.gather(res, [1],
    axis=1).mul(0.59)).add(tf.gather(res, [2], axis=1).mul(0
    .11));return res.div(255);}",
  "postprocess": "func/tensor-raw",
  "postprocessFunction": "async function postprocess(res)
    {probs = await tf.softmax(res).data();let i = probs
    .indexOf(Math.max(...probs));return i;}"
}
```

Figure 3. A sample configuration file

The example *config.json* file is built for a classifier model that was trained on 3-channel handwritten number images from the MNIST dataset and returns the predicted number. The model expects an input with the shape of *1 x 1 x 28 x 28*, but ideally, one would expect a user to submit an image to the model. So, in order to facilitate that, we put *img* as the input type, but that design choice comes with an expense. We now need to *preprocess* the input that we assume to be an image that is *28 x 28*. As in config tables in Appendix, the image will be read from an HTML *canvas* and will have four channels, so in order to reduce the image to only one channel, we implement *cv2.cvtColor* with *cv2.COLOR_BGR2GRAY* from *python-OpenCV* in TensorFlow.js while avoiding the fourth channel and normalizing the input by dividing it by 255. Since we only dealt with tensors and our end product for the *preprocess* was a tensor as well, we could choose *"func/tensor-tensor"* as the *preprocess* type. Note that other *preprocess* types might as well work without a hassle here, but our selection was a convenient one for our use case.

Furthermore, we will need to output a number that is the predicted handwritten digit from the image, so our output type should be *raw*. Our model outputs a vector with the shape of *1 x 10* that comprises the probability of each digit before the tf.*softmax*. So, in *postprocess*, we run *softmax* over our output and then convert it to an array. Finally, we find the maximum value's index, which is the value our network has predicted, and return that. Since we chose to use TensorFlow.js's *tf.softmax* function, it is more convenient for us to expect a *tf.tensor* into the *postprocess* function. Finally, since we output a number, we end up choosing *"func/tensor-raw"* as the postprocessType.

2.3. System Modules

In this subsection, we will provide details for the core system modules including the user management, model management, administration and compute modules. The EarthAIHub provides detailed documentation for users to learn how to build submissions for the platform, from creating the config file to converting models in various numerical computing libraries to TensorFlow.js models. In order to refrain from redundancy, we refer reader to the Docs for further details of the platform and usage.

2.3.1. User Management Module

EarthAIHub is designed as a community-driven platform; thus, authorization and authentication of users is an integral part of the system. To facilitate these, we used JSON Web Tokens (JWTs), which is a proposed internet standard. A JWT is a signature of a user. In authentication, a JWT should be generated by an authority and returned to the user once they provide a set of credentials, such as a username and a password, successfully. Thus, instead of expecting a user to log in every time they make a request or keep session information in the browser, a JWT could be used to authenticate and authorize a user. Based on this widely used methodology, the platform implements an authentication and authorization system that only expects a username and a password from the user. Furthermore, the User table in the database implements an administration functionality where users with an *is_admin* flag are able to carry out certain tasks such as approving and rejecting submitted models. All the fields a User table in the database holds can be seen in Table A6 in the appendix.

<u>User Creation:</u> User creation is carried out by filling out a registration form consisting of a username and two password fields. Once a user submits the registration form, the client-side validates that both passwords are the same. The server-side first checks if a user with the given username already exists. If the user does not exist, it creates a new user entry in the database, saving the password encrypted with SHA256.

<u>User Login:</u> Login functionality on the client-side is twofold: POSTing the entered credentials to the server-side, and saving returned JWTs on the client-side when login is successful. However, the server-side handles a more crucial operation once it confirms that the given credentials are correct. The server-side component creates a pair of JWTs for the given user: an access token and a refresh token upon login. An access token is a short-lived JWT, typically for 15 minutes. It can be used to perform actions throughout the web application that need authorization. On the other hand, a refresh token is a relatively long-lived JWT, typically for 30 days, that can only be used to refresh the access token with a new one. Once these tokens are created, they are sent to the client-side. Knowing the login was successful, the client-side application saves these two tokens as cookies with expiration dates and prompts the user that the login was successful.

From that moment on, whenever the client-side needs to make a request that needs authentication, it POSTs the access token as a header along with other data to the server-side. However, since the access token is short-lived, a new mechanism is needed to refresh the access token when it is about to expire or has expired already. That is ensured by a function that is run on the client-side right before every request that needs to be authorized. To facilitate this, there is a specific route on the server-side that checks if the used JWT is an access token and is still valid. If the current access token saved on the client-side cannot pass this check, the client-side scripts then proceed to refresh the access token by requesting a token from the refreshing endpoint on the server-side with the refresh token as a header in the request. If that endpoint rejects the provided refresh token, then it means either the provided refresh token is corrupt, or it has expired. In either of these cases, the client-side gets an error message from the server-side, deletes all JWTs from cookies, and redirects to login. How JWTs encrypt user information, validate them, and separate access tokens from refresh tokens will not be discussed here as we believe these are beyond the scope of this study. We refer the reader to the JWT documentation (Auth0, 2022) to better understand these concepts.

<u>User Dashboard:</u> The User Dashboard is an interface on the client-side. In communication with the Model Management Module, a logged-in user can see and access their submitted models, see their approval status, and change their password on that interface.

2.3.2. Model Management Module

The Model Management Module in the platform manages model creation and access to those models. While anyone could run any of the models approved by an admin on the app, only registered users could create a model. Full database specifications of a model can be seen in Table A7 in the Appendix.

<u>Model Creation:</u> A user should input the necessary information about the model they are submitting alongside the necessary model files, i.e., the archive file of the TensorFlow.js GraphDef model and the config.json file that we have described earlier. As for the information the user provides regarding the model, EarthAIHub asks for a name, a description of the model, some brief information about the input and output that the model expects and delivers, and

finally, an optional extended information text to include any relevant links and publications. Once a user fills out the form and submits it, the client-side Model Management Module makes a POST request to the server-side with all the information and files provided and attaches the JWT access token to that request. The server-side part of things is straightforward; both files are saved in the static file directory of the platform with random hexadecimal names; both unarchived and archived versions of the model are stored. After that, the paths to the saved files and the model information, along with the submitting user's identity, are saved to the database.

Models Page: The *Models* page is an interface where everyone can see all submitted and approved models, whether they are logged-in users or not. Once a user gets to the Models page, the client-side Model Management Module makes a GET request to the server-side Model Management Module without an authorization header. Those models are returned to the client-side without actual model files but with their paths in the app. This way, the burden on both the server-side and client-side steps is minimized because model files should only be downloaded to the client-side when needed, which is not until a client decides to try out a model on EarthAIHub.

Individual Model Page: On EarthAIHub, each model has its own page accessible through the *Models* page. To facilitate running models, the platform's Model Management Module renders an input box according to the submitted config on the model page. Also, for the same purpose, a button to run the model and a selection box that allows users to select which backend they want to use to run the model (either CPU or WebGL) are visible. Once a user runs the model after choosing their input file or typing in the input, the Compute Module that will be described below takes over, and once it is done with the running, the Model Management Module renders the output on the model page according to the config file. On the Individual Model Page, the owner of individual models finds a link to edit their submission. The editing interface is similar to the model submission interface with minor differences; a user must describe the changes in an external text box to ease administration. Once an edit is submitted, the model is again saved as *is_approved=0* and needs the attention of an admin.

2.3.3. Administration Module

Being a community-driven platform, EarthAIHub relies on submissions and therefore is prone to misuse. In order to form a middleware between submissions and end-users, the platform facilitates an administration layer. An admin is defined as a User in the database with a flag (*is_admin*) in the table. Every model has an *is_approved* field, and every model submitted to the system is saved to the database with "Pending" status that will be approved by admins.

Admin Dashboard: On the admin dashboard, all models that require approval are listed. Admins could go through these models and make a decision about them. For the most part, similar to *Models* page, on the admin dashboard, each listed model has a link to an individual model page.

The minor differences are for only admins to see and use to make decisions on submitted models. If an admin decides a model is adequately submitted, they could change the status to "Approved", making its *is_approved* field 1. They could also reject a model to alter its database entry to be *is_approved=2*. However, they also need to provide an explanation for their decision using the text box placed there for further decision-making purposes. Once a model is rejected, the user who submitted that model sees its rejected status in their dashboard and the rejection reason in the editing interface. Thus, they could edit that model accordingly for resubmission, which ultimately would create a new task for admins. Along with models that need attention, admins can also see models they made a decision on in their Admin Dashboard. That design choice was made to make it easier for admins to see if models they rejected before are resubmitted.

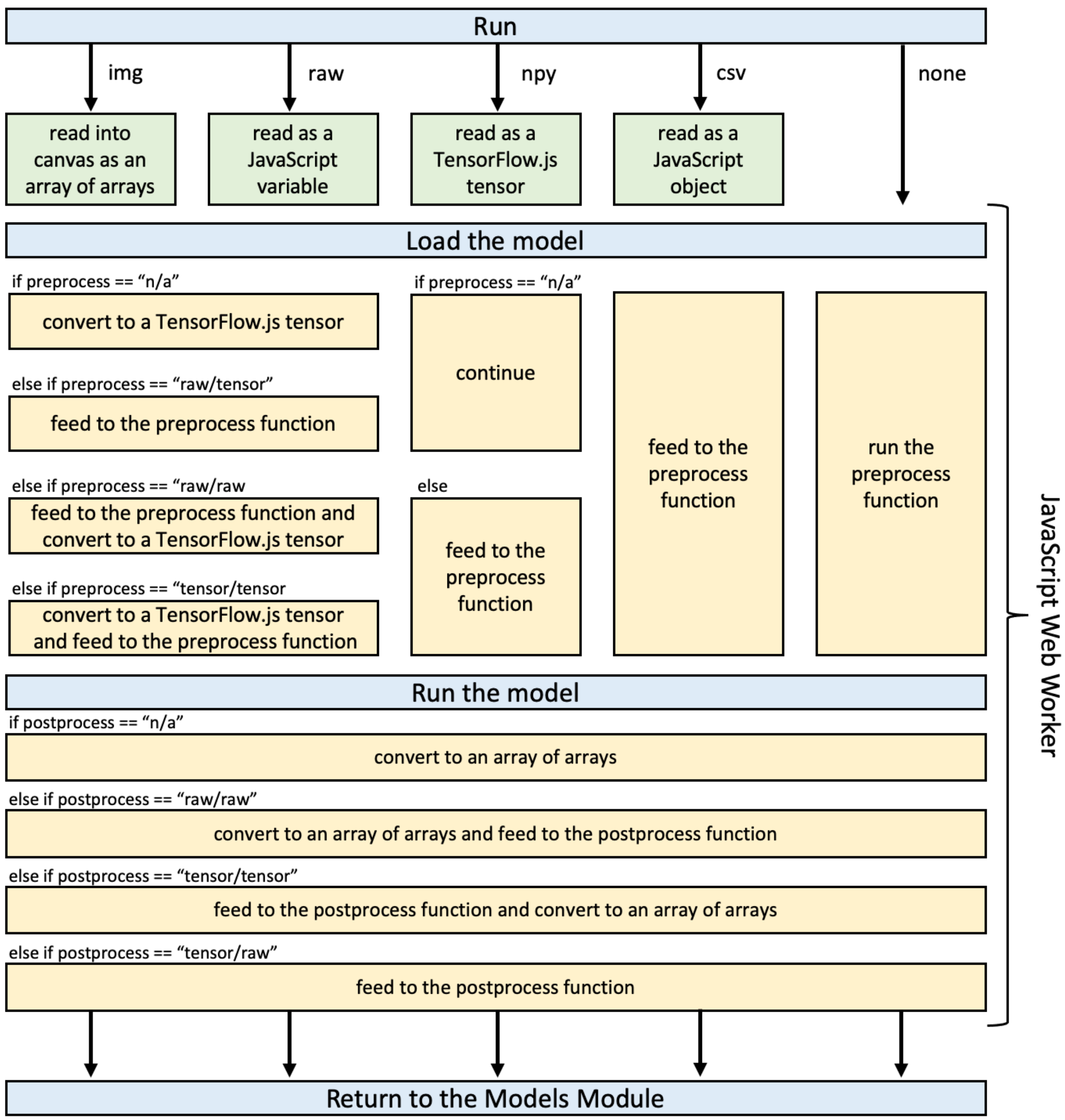

Figure 4. Compute Module schema

2.3.4. Compute Module

The Compute Module is where client-side computing capabilities are utilized. When a user enters an Individual Model Page, the Compute Module loads the config file simultaneously with the Model Management Module. After the user enters their input (if applicable), the Compute Module is initiated once the user decides to run the model. The module starts by reading the input if the config states the existence of an input. How the input is read depends on the input type, but at the end, the input is stored as a JavaScript variable. Once the input is read, the client-side computing resources are put to use. In order to do so without interfering with how the interface of EarthAIHub works, we implemented a JavaScript Web Worker. A web worker is created right after the input is read. The input, configuration of the model, and the location of the TensorFlow.js model file are communicated to the worker right after the worker is created.

The worker first imports TensorFlow.js and the TensorFlow.js GraphDef model and then runs preprocessing on the input variable depending on the specifications defined in the config file. After that, the worker feeds the preprocessed (if applicable) input to the imported model. Once the model's output is obtained, the worker then runs postprocessing over the output, again according to the specifications in the config. After the postprocessing, the output is then converted to a vanilla JavaScript variable and communicated back outside of the worker's scope. Output is specifically transferred in such a format because (a) we do not import TensorFlow.js outside of the worker's scope, and (b) sending messages to and receiving messages from a web worker does not support external object types. Finally, the Compute Module gives the output back to the Model Management Module to render it according to the config. The workflow of the Compute Module can be seen in Figure 4.

2.4. User Interface & Scenarios

In this subsection, we will go through some common user scenarios. Besides being a registered user of EarthAIHub, submitting a model to the platform needs a clear understanding of the configuration format. Once a researcher has their model in TensorFlow.js GrapDef format, also known as SavedModel, they need to make sure their model works flawlessly even without the platform. Then the next step would be to prepare the config file as described in Subsection 2.2 and the Appendix. When both the model file and the config are ready, one could quickly fill out the submission form and create a task for admins (Figure 5).

Previously submitted and approved models can be seen by any user of the web application through the navigation bar. Once a user sees the list of already submitted and approved models, they can choose the one they prefer and go to the individual model page to run the model. If the model needs any input, the user will upload their input, select the backend, and run the model. After model computation, the result would appear in the result section of the model page.

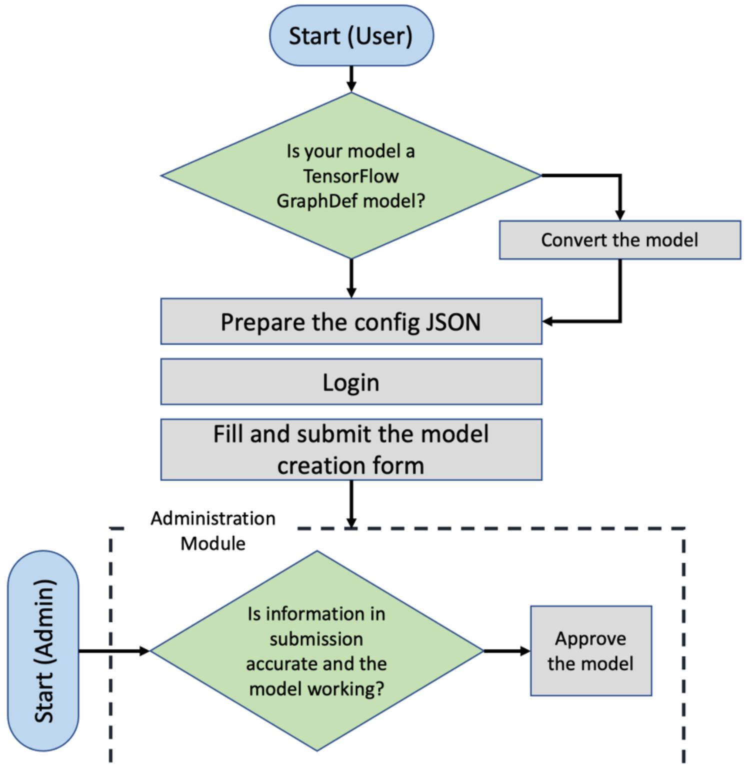

Figure 5. Model creation/submission workflow

3. Results and Discussions

Many applications from many scientific disciplines could be run on EarthAIHub, as deep learning applications are not limited to any specific field. However, per the goal of this study, we want to draw attention to deep learning applications in the earth and climate sciences, as deep neural networks have been used in various tasks within these disciplines, and we aim to provide a go-to platform on which domain scientists can obtain an understanding. This section demonstrates how the platform can be utilized for various deep learning applications. For each model, we first introduce the model and then refer to the necessary EarthAIHub config in the Appendix for that model. Most of the models here will be research done in hydrology, but also to prove the concept, we put the platform to use for various state-of-the-art deep learning models in common application areas.

3.1. Generic Use Cases

3.1.1. Emotion Detection with FER+

Facial expression recognition has been a task of interest in computer vision even before the comprehensive utilization of deep neural networks for this purpose. FER+ (Barsoum et al., 2016) is an annotation dataset where various images that depict human faces with facial expressions are labeled. This model is a deep Convolutional Neural Network (CNN) (LeCun and Bengio, 1995) that was trained on FER+ using the CNTK (Seide and Agarwal, 2016) numeric computing library and was provided for public use in the ONNX GitHub repository. We converted this

ONNX model to a TensorFlow.js GraphDef model and built a config file that wraps the model in order for it to be run on EarthAIHub. The model on EarthAIHub expects a 64x64 image and returns probabilities for eight different emotions. The config file for this model can be seen in Appendix B1.

3.1.2. Image Classification with EfficientNet-Lite4

EfficientNet (Tan and Le, 2019) is a convolutional neural network architecture that changes how scaling is done for neural networks. The EfficientNet-Lite4 is a CNN that is trained on ImageNet (Deng et al., 2009) and achieves state-of-the-art accuracy. One upside of EfficientNet-Lite4 is that it is designed to work on devices with limited computational capabilities, thus making it a great candidate to run on the web. The model on EarthAIHub expects an image of 224x224 and outputs five ImageNet categories with top probabilities. The trained model that was trained on the COCO 2017 (Lin et al., 2014) dataset, was obtained from the ONNX GitHub repository. The model was converted to the TensorFlow.js GraphDef model. The config file for this model can be seen in Appendix B2.

3.1.3. Handwritten Digit Recognition from MNIST

MNIST (Deng, 2012) is a handwritten digit image dataset widely used for educational and benchmarking purposes in computer vision. This model is a pretrained CNN over the MNIST dataset that reaches a top-1 error rate of 1.1%. The model was obtained from the ONNX model zoo at the ONNX GitHub repository and then converted to a TensorFlow.js GraphDef model. The model takes a matrix of 28x28, but the inputting image interface on EarthAIHub reads images with four channels; consequently, the config was designed accordingly. The preprocess function transforms the submitted image into one channel using the cv2.COLOR_BGR2GRAY implementation on opencv-python (Bradski and Kaehler, 2000), avoiding the fourth channel. The config file for this model can be seen in Appendix B3.

3.1.4. Image Classification on CIFAR-10

CIFAR-10 (Krizhevsky and Hinton, 2010), like MNIST, is a popular dataset among deep learning practitioners and researchers, making it an excellent go-to dataset for training and demonstrating the promise of deep learning-related works.We followed the "Deep Learning with PyTorch: A 60 Minute Blitz > Training a Classifier" tutorial for this model and trained a CNN over CIFAR on PyTorch. Then we converted the PyTorch model to a TensorFlow.js one. The config file for this model can be seen in Appendix B4.

3.2. Earth & Climate Sciences Use Cases

3.2.1. LiDAR Super-resolution

Light Detection And Ranging (LiDAR) is a remote sensing method to map the elevation of terrains or surroundings. In earth sciences, it is widely used in various modeling and geospatial analysis studies including water delineation (Sit et al., 2019), flood forecasting and mapping (Hu and Demir, 2021), and higher resolution LiDAR data is crucial. This model is a pretrained model defined in Demiray et al. (2021a) and takes a 25x25 raw JavaScript array of arrays and increases the resolution to 400x400. The config file for this model can be seen in Appendix B5. A set of examples of low resolution and high resolution DEMs, and the output of the DSRGAN can be seen in Figure 6.

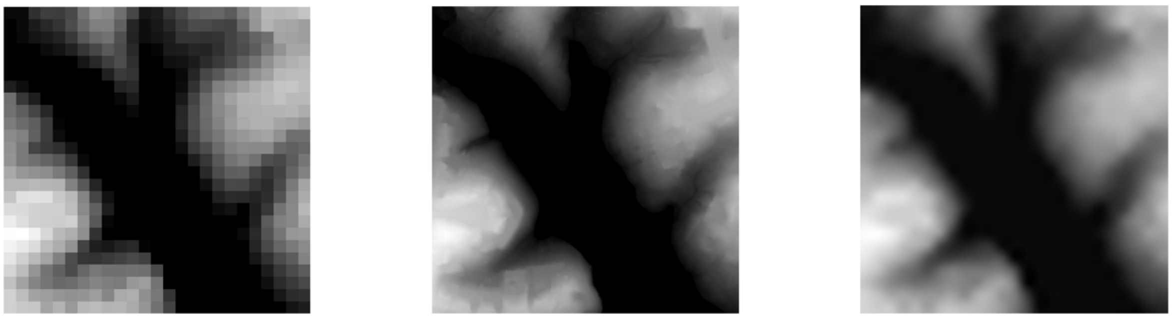

Figure 6. (a) Low resolution DEM, (b) high resolution DEM and (c) generated high resolution DEM by DSRGAN

3.2.2. Generating New Satellite River Imagery

Data generation with deep neural networks is one of the approaches that has not been widely explored in water resources and climate research. However, one study explores generative adversarial networks (GANs) (Goodfellow et al., 2020) in satellite river imagery generation. This model we show as a use case here is a pre-trained version of the Progressively Growing GAN (Karras et al., 2017) model with the dataset presented in Gautam et al. (2020) that outputs a randomly generated bird's eye river image. Since this is a generation task from a random noise vector, the config file was created accordingly. The config file for this model can be seen in Appendix B6. A generated 1024x1024 river image from a random vector on EarthAIHub can be seen in Figure 7.

3.2.3. Flood Forecasting with NRM

Flood forecasting has been a vital task in hydrology. Beyond physical modeling, various approaches have been tried to tackle this task with both conventional machine learning models and deep learning (Sit and Demir, 2019). This model was introduced by Xiang and Demir (2020) and utilizes Long short-term memory (LSTM) (Hochreiter and Schmidhuber, 1997) networks for 24 hours of rainfall-runoff forecasting. The model was trained on Keras for a USGS streamflow station in Iowa, United States and then converted to a TensorFlow.js model. The config was created to read a CSV file for all the data that the model expects. The config file for this model can be seen in Appendix B7. An example forecast for 24 hours of input and 24 hours of output runoff is visualized on a line chart in Figure 8.

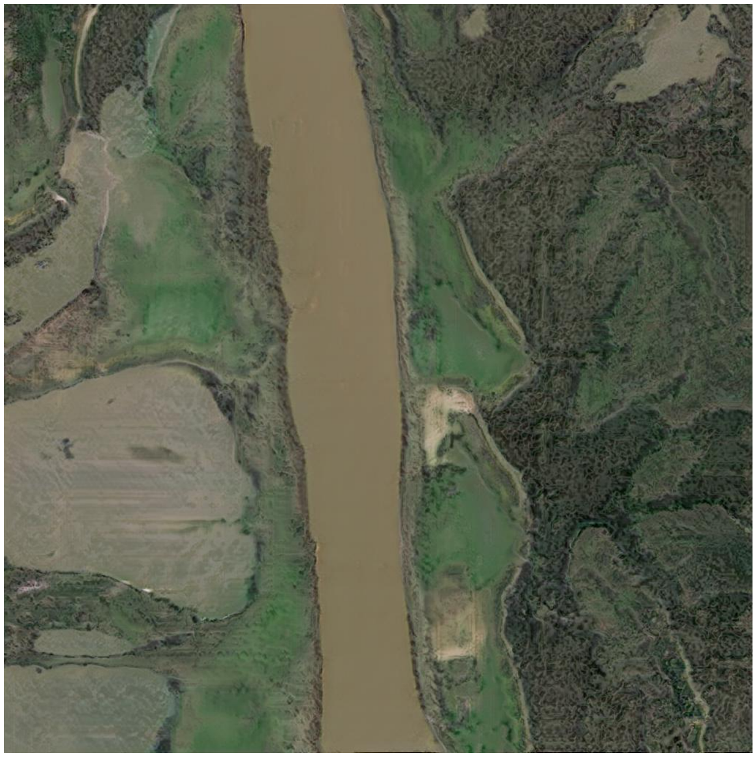

Figure 7. An example output of river image generation GAN (Gautam et al., 2022)

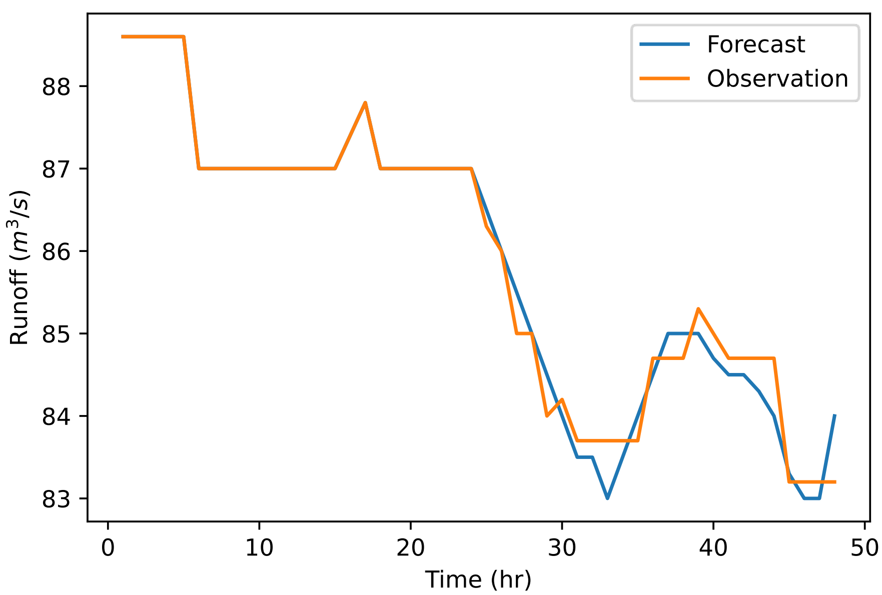

Figure 8. Input/Outuput lines for a streamflow data sequence of 48 hours

4. Conclusions

This study presented EarthAIHub, a community-driven web platform where practitioners and researchers make their deep learning applications accessible and end-users experience how deep learning research in earth science and climate domains works. In order to achieve a generalized platform that can run many different deep learning models, we created an abstraction layer, a middleware, that is, a configuration file between specific deep learning models and end-users based on a JSON file. The config file works to make the EarthAIHub understand individual models. In order to show both the capabilities of the web application and how various models with different input-output types could be formatted to run on the platform, we provided seven use cases. Even though we mostly showed computer vision applications as they are easier to visualize, we also demonstrated that the platform is able to provide a medium for models with various goals, such as time series forecasting and super-resolution applications.

As of now, EarthAIHub is designed to run only TensorFlow.js models. It is not always possible to convert a model that has been trained in one programming language and framework pair to TensorFlow and later TensorFlow.js. For instance, in order to convert a PyTorch model to a TensorFlow.js model, one needs to convert that model to ONNX, TensorFlow, and finally TensorFlow.js consecutively. Moreover, some implementations of some architectures are not always available in all of these libraries. For instance, some recurrent neural network structures in PyTorch are implemented differently than they are in TensorFlow. Consequently, one could easily have problems when converting that model to TensorFlow.js. The coverage of models and architectures could be extended by incorporating other numeric computing and deep learning libraries in JavaScript, such as ONNX Runtime Web. One downside of not implementing ONNX Runtime Web into EarthAIHub during this study was, as mentioned earlier, that ONNX Runtime Web is still not fully developed for practical web applications.

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Appendix

Table A1. Fields and their definitions for the config file

Field	Description
name	The name of the model, for reference purposes only, is not used in the execution.
input	Defines the type of the input. EarthAIHub enables you to easily run various types of inputs. The model page is rendered to ask the end-user to put in or upload the selected input type. For each input type, there is a range of preprocessing function types available. Please refer to Table A2 for the available input types.
preprocess	This field should be filled with one of the input-specific *preprocess* options. Please refer to Table A3 for available *preprocess* options for each input type.
preprocessFunction	A function is defined as a string. The function name must be preprocess, take an input (even if the input type is none), and return an output.
output	Defines the type of the output. The output could be *img* or *raw* to return the output the model produces in the correct format to the end-user. For each output type, there is a range of post-processing function types available. Please refer to Table A4 for the available output types.
postprocess	This field should be filled with one of the output-specific *postprocess* options. Please refer to Table A5 for available postprocess options for each output type.
postprocessFunction	A function is defined as a string. The function name must be postprocess, and it must take an input and return an output.

Table A2. Input types and their definitions

Input Type	Description
img	Input is a single image read in 4 channels by an HTML canvas, and the end-user uploads an image.
raw	A *textbox* is rendered so the end-user can input whatever they want to be read into a JavaScript variable using *eval()*.
npy	An *npy* file that carries exported NumPy (Harris et al., 2020) arrays is needed. The input is always converted to a tf.tensor upon reading.

csv	A *csv* file upload is needed; the uploaded *csv* file will be read as a JavaScript *object*.
none	Nothing is expected as the input, and a preprocessing function must be defined. Whatever the preprocessing function returns is fed to the *GraphDef* model. The preprocess field in the config does not need to be defined.

Table A3. Input types and available preprocessing types for each of the input types

Input Type	Preprocess Option	Description
img	**n/a**	No preprocessing function will be provided; the input will be fed into the model as-is. Typically not the case.
	func/raw-tensor	The input to the *preprocess* function is the raw input format, which is an array of arrays for *img*. The output of the *preprocess* function is assumed to be a *tf.tensor*, so if a user chooses to use this option in the config, they need to be sure that their *preprocess* function returns a tensor.
	func/tensor-tensor	The input to the preprocess function is a *tf.tensor*. The output of the preprocess function is also assumed to be a *tf.tensor*, so if a user chooses to use this option in config, they need to be sure that their preprocess function returns a *tf.tensor*.
	func/raw-raw	The input to the preprocessing function is the raw format of the input, which is an array of arrays for *img*. The output is also in raw format, which could be anything but a *tf.tensor.* The system will handle conversion to the tensor before feeding the output of the *preprocess* function by running *tf.tensor()* on the output.
raw	**n/a**	No preprocessing function will be provided; the input will be fed into the model as-is. Typically not the case.
	func/raw-tensor	The input to the *preprocess* function is the raw format of the input that is the output of the *eval()* when run on the content of the textarea for the raw. The output of the *preprocess* function is assumed to be a *tf.tensor*, so if a user chooses to use this option in the config, they need to be sure that their preprocess function returns a tensor.
	func/tensor-tensor	The input to the *preprocess* function is a tf.tensor. The

		textarea is fed to *tf.tensor(eval(...))*, and the result is fed to the model. The output of the *preprocess* function is also assumed to be a *tf.tensor*, so if a user chooses to use this option in the config, they need to be sure that their *preprocess* function returns a *tf.tensor*.
	func/raw-raw	The input to the *preprocess* function is the raw format of the input that is the output of the *eval()* when run on the content of the *textarea* for the raw. The output is also in raw format, which could be anything but a *tf.tensor*. The system will handle conversion to the tensor before feeding the output of the *preprocess* function by running *tf.tensor()* on the output.
npy	**n/a**	No *preprocess* function will be provided; the input will be fed into the model as-is.
	func/raw-tensor	The input to the *preprocess* function is a *tf.tensor*. The output of the *preprocess* function is assumed to be a *tf.tensor*, so if a user chooses to use this option in the config, they need to be sure that their *preprocess* function returns a tensor.
csv	**func/raw-tensor**	The input to the *preprocess* function is a JavaScript object defined by the *csv* file read. The output of the preprocess function is assumed to be a *tf.tensor*, so if a user chooses to use this option in the config, they need to be sure that their preprocess function returns a *tf.tensor*.
none	**n/a**	Preprocess type does not have to be defined, but a preprocessFunction must be given.

Table A4. Output types and their definitions

Output Type	Description
img	The output of the model or postprocess function (if applicable) has to be a *tf.tensor* shaped *1 x 3 x w x h* so that it can be rendered.
raw	The model output is rendered as-is on the page.

Table A5. Output types and available postprocessing types for each of the output types

Output Type	Postprocess Option	Description
img	**n/a**	There is no *postprocess* function defined. The model's output is converted to an array by *arraySync()* and put on an HTML *canvas* to render as an image.
	func/raw-raw	The model's output is converted to an array by *arraySync()*, and then the *postprocess* function is run. The output of the *postprocess* function should also be something but a *tf.tensor*, so it would get rendered on an HTML *canvas* after the *postprocess*.
	func/tensor-tensor	The output of the model is fed to the *postprocess* function. The output of the *postprocess* function should also be a tensor which is then converted to the raw format by *arraySync()* and rendered on an HTML *canvas*.
	func/tensor-raw	The output of the model is fed to the *postprocess* function. The output of the *postprocess* function should be something but a *tf.tensor*, so it would get rendered on an HTML *canvas* after the *postprocess*.
raw	**n/a**	There is no *postprocess* function defined. The model's output is converted to an array by *arraySync()* and rendered as-is.
	func/raw-raw	The model's output is converted to an array by *arraySync()*, and then the *postprocess* function is run. The output of the *postprocess* function could be anything but a tensor so that it would get rendered after the *postprocess*.
	func/tensor-tensor	The output of the model is fed to the *postprocess* function. The output of the *postprocess* function should also be a *tf.tensor*. The output of the *postprocess* function is then converted to the raw format by *arraySync()* and rendered.
	func/tensor-raw	The output of the model is fed to the *postprocess* function. The output of the *postprocess* function should also be something but a *tf.tensor*, so it would get rendered after the *postprocess*.

Table A6. Fields and their types for the User table in the database.

Field	Type
id	Integer
username	String
password	String
is_admin	Boolean
timestamp	DateTime

Table A7. Fields and their types for the Model table in the database.

Field	Type
id	Integer
owner	String
name	String
description	Boolean
input_output	String
more_info	String
model_file	String
config_file	String
is_approved	Integer
approving_mod	String
notes	String
timestamp	DateTime
updated	DateTime

B. Configuration Files

B1. Emotion Detection with FER+

```
{
	"name": "FER+",
	"input": "img",
	"output": "raw",
	"preprocess": "func/tensor-tensor",
	"preprocessFunction": "function preprocess(res) {res=tf.gather(res, [0], axis=1).mul(0.3).add(tf.gather(res, [1], axis=1).mul(0.59)).add(tf.gather(res, [2], axis=1).mul(0.11));return res;}",
	"postprocess": "func/tensor-raw",
	"postprocessFunction": "async function postprocess(res) {probs = await tf.softmax(res).data();return {'neutral':probs[0], 'happiness':probs[1], 'surprise':probs[2], 'sadness':probs[3], 'anger':probs[4], 'disgust':probs[5], 'fear':probs[6], 'contempt':probs[7]};}"
}
```

B2. Image Classification with EfficientNet-Lite4

```
{
	"name": "EfficientNet-Lite4",
	"input": "img",
	"output": "raw",
	"preprocess": "func/tensor-tensor",
	"preprocessFunction": "function preprocess(res) {res=tf.gather(res, [0, 1, 2], axis=1);res=tf.einsum('bcij->bijc', res);return res.sub(127).div(128);}",
	"postprocess": "func/tensor-raw",
	"postprocessFunction": "async function postprocess(res) {labels={...};probs = tf.softmax(res);topkIndices = await probs.topk(5).indices.data();var categories=[];for (var i = 0; i < topkIndices.length; i++) {categories.push(labels[topkIndices[i]]);};return categories;}"
}
```

B3. Handwritten Digit Recognition from MNIST

```
{
	"name": "MNIST",
	"input": "img",
	"output": "raw",
	"preprocess": "func/tensor-tensor",
```

```
	"preprocessFunction": "function preprocess(res) {res=tf.gather(res, [0], 
axis=1).mul(0.3).add(tf.gather(res, [1], axis=1).mul(0.59)).add(tf.gather(res, [2], 
axis=1).mul(0.11));return res.div(255);}",
	"postprocess": "func/tensor-raw",
	"postprocessFunction": "async function postprocess(res) {probs = await 
tf.softmax(res).data();let i = probs.indexOf(Math.max(...probs));return i;}"
}
```

B4. Image Classification on CIFAR-10

```
{
	"name": "CIFAR",
	"input": "img",
	"output": "raw",
	"preprocess": "func/tensor-tensor",
	"preprocessFunction": "function preprocess(res){res=tf.gather(res, [0, 1, 2], 
axis=1);return res.div(255).sub(0.5).div(2);}",
	"postprocess": "func/raw-raw",
	"postprocessFunction": "function postprocess(res){classes = ['plane', 'car', 'bird', 
'cat', 'deer', 'dog', 'frog', 'horse', 'ship', 'truck'];let i = 
res[0].indexOf(Math.max(...res[0]));return classes[i];}"
}
```

B5. LiDAR Super-resolution

```
{
	"name": "LiDAR",
	"input": "raw",
	"output": "raw",
	"preprocess": "func/tensor-tensor",
	"preprocessFunction": "function preprocess(res) {return 
tf.expandDims(tf.expandDims(res, axis=0), axis=0).div(1000);}",
	"postprocess": "func/tensor-tensor",
	"postprocessFunction": "function postprocess(res) {return 
res.squeeze().mul(1000);}"
}
```

B6. Generating New Satellite River Imagery

```
{
```

```
    "name": "RiverGAN",
    "input": "none",
    "output": "img",
    "preprocess": "func/tensor-tensor",
    "preprocessFunction": "function preprocess(res) {return tf.randomNormal([1,
512]);}",
    "postprocess": "func/tensor-tensor",
    "postprocessFunction": "function postprocess(res) {return
res.add(1).div(2).mul(255);}"
}
```


B7. Flood Forecasting with NRM


```
{
    "name": "NRM",
    "input": "csv",
    "output": "raw",
    "preprocess": "func/tensor-tensor",
    "preprocessFunction": "function preprocess(res){enc_q =
tf.tensor(res[0]).div(10000);enc_pcp = tf.tensor(res[1]).div(200);enc_et =
tf.tensor(res[2]);dec_pcp = tf.tensor(res[3]).div(200);dec_et = tf.tensor(res[4]);enc =
tf.concat([enc_q, enc_pcp, enc_et], 0);dec = tf.concat([dec_pcp, dec_et], 0);return [dec,
enc];}",
    "postprocess": "func/tensor-tensor",
    "postprocessFunction": "function postprocess(res){return res.mul(10000)}"
}
```