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Board 90: Core Feature Extraction with Computer Vision

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I am completing my bachelors in computer science at CSU, Bakersfield. My primary interest is in Artificial Intelligence. I am currently conducting research in Computer Vision. Particularly, using AI in order extract valuable data from Core slabs in order to improve the energy industry. In the future, I would love to pursue a Masters degree in the field of Artificial Intelligence and apply my knowledge to solve problems around the world.

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CORE FEATURE EXTRACTION WITH COMPUTER VISION

I. Introduction

This work details the senior project capstone experience of a group of undergraduate students at the California State University, Bakersfield (CSUB), a medium-size, comprehensive, Hispanic Serving Institution (HSI). The work is novel and potentially commercializable in the field of energy conversion and petrochemical extraction. A thorough description of their methodology is provided, and their results show promise. In addition, we discuss the curriculum and project management structure that enabled an undergraduate senior project group to interface with oil and gas companies to source data needed to carry out their project.

In the oil and gas industry, exploration is largely dependent on the study of the subsurface hundreds or thousands of feet below. Most of the data used for this purpose is collected using borehole logging tools. Although sophisticated, these tools are limited as to how precisely they can measure the subsurface in terms of vertical resolution. There is one method of studying the subsurface that provides unlimited vertical resolution – core samples. Although core samples provide scientists the opportunity to generate a full, continuous data set, lab analysis work is normally done at one-foot intervals, as anything more would be prohibitively expensive. This means at best a representative data set is generated. However, if the subsurface is not homogeneous, it is difficult to generate a representative data set with lab analysis done at one-foot intervals. This is a void that artificial intelligence can fill. More specifically, a properly trained neural network can perform a continuous analysis on high-resolution core images from top to bottom. It is also important to note that geologic interpretation tied to core analysis can introduce human error and subjectivity. Here too, a properly trained neural network can generate results with extreme levels of accuracy and precision. One core analysis expert believes that core analysis done manually is flawed about 70% of the time [1]. This flawed analysis can result from lack of experience and or a lack of knowledge of the geologic formation. We experiment with convolutional neural networks (CNN) for our senior project capstone experience to determine if it is applicable for a continuous data set analysis. A CNN is an area of deep learning that specializes in pattern recognition. A pre-trained CNN can be re-tooled to detect oil saturation in core images.

We are not the first to attempt to analyze core samples with vision algorithms [2] [3] [4]. It is well known that training a neural network requires abundant data, thankfully through industrial partnerships we've obtained hundreds of core images sufficient to train a neural network, as well as core interpretations tied to those images coming from a core analysis expert with over 40 years of experience. There have been attempts to integrate neural networks into the oil and gas industry since the 1990s [5] [6], although in those times the algorithms and the image quality required for our experiments were inadequate, until now. Our early experimental results are promising, with the neural networks returning an average final accuracy of 85% for ultraviolet light images, and 78% for white light images. Its important to note that this level of accuracy can not be replicated by a human core analyst using only images.

We present a method for integrating Project-Based Learning (PBL) in senior project/capstone experiences [7]. Conventionally, students select a project and implement it as a mock-up or trial of a real-world product. PBL is a student-centered teaching approach that requires them to solve a real-world problem or challenge. Students engage in an extended, interdisciplinary process of inquiry in response to solve this problem or challenge. Most senior project/capstone experiences for many decades follow PBL in some way. We revisit this topic to focus on inquiry-based learning, a core concept of PBL. Senior project activities are not automatically inquiry-based learning. Activities in senior project courses are often the opposite: teacher centric learning. In a departure from previous practices at CSUB, this is among the first efforts to involve industry input in a project, which may be more common at other engineering or polytechnic universities.

II. Related Work

II.A. Related Works in Core Analysis and Automation

A group of petroleum engineering researchers at the University of Kansas designed two distinct CNNs to measure oil saturation, lithology (general rock physical characteristics), and fracture analysis [4]. It is mentioned that their CNN did not perform validation while ours do. They used white light and ultraviolet images as a combined input to the CNN, while we train our networks with either white or ultraviolet light, independently. Additionally, there is never any mention of the amount of core slab images they were able to source for the study, or the origin of the core slab images. Their publication lacks crucial information needed for reproducibility.

A group of Stanford researchers used micro-computed tomography (micro-CT) and Scanning Electron Microscopy (SEM) images of core samples to assess the porosity of core samples [3]. While promising, SEM and micro-CT equipment are very expensive. More importantly it is not a standard industry practice to collect these types of images, making them rare. This presents a significant challenge since neural networks require ample amounts of data. To combat this the researchers used StyleGANs. A StyleGAN is a generative adversarial network (GAN) that is used to generate high-resolution, synthetic images. StyleGAN vectors are used to control different aspects of the image such as color, shape, and texture. Specifically, they are used to generate images like the input in the case of the Stanford study. This helps data augmentation tremendously and ensures that enough data prevents overfitting the neural network. Our approach does not suffer from the use of synthetic images. Instead, we sourced a wide range of high-quality images to train the neural networks, ensuring that our results are representative of real data.

One other work applied CNNs to a GIS based regional saturation system [8], but our work is significantly different. Their work aimed to predict future oil saturations from historical context, while our work aims to characterize the petroleum reservoir at the subsurface interval where the core was acquired.

Another noteworthy work like ours involved the use of ResNeXt-50 CNN to automatically identify lithology [2]. In testing they found their trained model predicted the lithologies of new core with an accuracy of 93.12%. We will expand upon their work by training our model with our own data set and use different neural networks to achieve the maximum accuracy possible.

Mohammed Misbahuddin of the University of British Columbia used CNNs to assess shale rock [9]. Shale rock is very tightly compacted and fine grained and is therefore difficult to analyze without special tools such as scanning electron microscopy (SEM) or focused ion beam-scanning electron microscopy (FIB-SEM). In this study a CNN is used to predict the properties form grayscale SEM images. Our study is different because we are interested in sandstones, which exhibit much more obvious features and do not require SEM images.

There is a group at the university of Texas at Austin, which proposes a "multiphysics workflow" for lithology classification [10]. This workflow involves well logs, computed tomography (CT) scans, and core analysis data. It should be noted that while well logs are available for virtually every newly drilled well, CT scans and core analysis are rarely done. Moreover, it is more rare to have a combination of all three. By not relying on CT scans, we are able to utilize a significantly larger dataset for our study.

Lastly, a study was done by researchers at the Skolkovo Institute of Science and Technology using various deep neural networks, similar to our study, to predict permeability of digitized rock samples [11]. Although we do not intend to extract permeability from our images.

II.A. Related Works in Education

PBL is a well-studied educational method. It has often been applied to senior project/capstone experiences. Darren et al. [12] describes a model for a centrifugal pump test bed, originally a senior project/capstone experience, that, after multiple design iterations, can be used for project-based learning laboratory activities in other classes. Alptekin et al. [13] discusses the design of a prototype product developed as part of a manufacturing engineering capstone course at the California Polytechnic State University. The product is an autonomous parafoil surveillance platform equipped with sensors, controllers, mechanical components, and software. The development of the product followed PBL principles. There are many such examples of PBL senior project experiences in literature [14], [15] and project learning is expected by the Accreditation Board for Engineering and Technology (ABET) for at least two decades [16]. The key features of PBL [7] are:

- A focus on a specific problem or challenge: PBL tasks are designed to simulate real-world problems or challenges that require students to apply critical thinking, problem-solving, and creativity.
- Collaborative learning: Students typically work in groups, with each member contributing their unique skills and perspectives.
- Student autonomy: Students have significant autonomy in designing and implementing the project, allowing them to take ownership of their learning and pursue their interests.
- Authentic assessment: Students are assessed based on the quality of their final product, as well as their ability to reflect on the learning process and apply what they have learned to other contexts.

Senior project/capstone experiences have long used PBL. However, we are interested in revisiting the topic to ensure that the course also follows inquiry-based learning, a core component of PBL. At CSUB, senior project/capstone experiences in the department follow a software-development paradigm like the waterfall method. The teacher and students select a product of some significance. They define a project, set goals, and work on sub-goals over the course of the class. Students give formal presentations on a frequent basis, where the students solicit feedback from the instructor about their progress. This is teacher centric, and the instructor plays the roll of the project manager and product stakeholder.

This work discusses ways to make the course more inquiry-based. The goal of the project is to explore a vague goal or question, *is it possible to detect oil saturation in core images?* Weekly meetings are held where students reflect on goals and determine if changes need to be made to the approach. The discussions are student-led and focus on implementation rather than assessment of presentation skills. An overview is given in Figure 1.

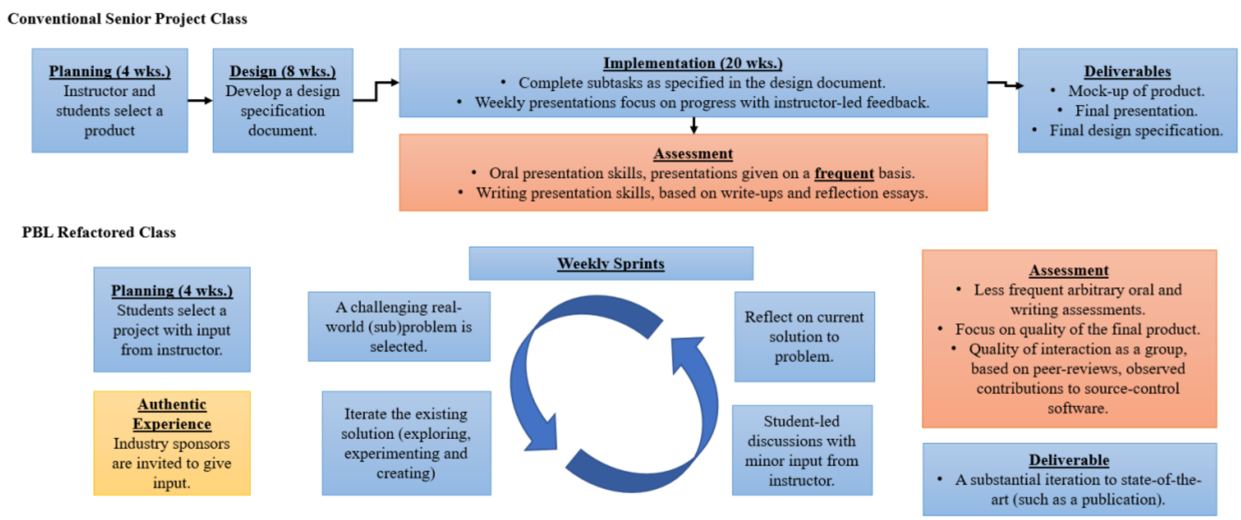

Figure 1: Comparison of conventional senior project/capstone experiences at CSUB and the refactored model using PBL.

III. Methods

III.A. Instructional Strategies

The senior project capstone experience at the university is a year-long sequence, where students take 2-units in the Fall and 2-units in the Spring. A single instructor oversees the project as a mentor. Generally, students consult with a faculty supervisor, investigate relevant literature, and prepare a substantial project of some significance. Students must work in teams. A key theme of the course is that students identify a problem, analyze it, and apply knowledge of computer science and propose a solution to the problem. The project is required to have intellectual merit similar to a competitive analysis in a business plan. Some of the key milestones for the conventional implementation of the course are:

- The premise of the project is a product based on need from market analysis.

- Completion of design specification document early on that specifies the tasks to be completed, such as a software requirements document.
- In class, students often give formal presentations to discuss progress. Though students drive the activity, it is still teacher centric. Students play a passive role listening to instructor feedback based on the presentation.
- Due to the passive mechanic of soliciting feedback from the instructor after presentations (and seeking their approval) the instructor is essentially operating as the product owner.
- Weekly sub-goals are based on the software requirements document, but minor changes can be made as issues are encountered during implementation.
- Written assignments (beyond the design specification) are technical and non-technical, such as broad reflection essays.

Assessment is based on performance on presentations and writing activities, and the deliverable is a final project presentation. Providing a complete product is expected but not a majority of their grade. The following changes are suggested for a more inquiry-based experience for students:

- The premise of the project is a vague question or obstacle to the state of the art.
- Students are required to have an authentic project by involving industry partners.
- A planning document is required but it is more like a literature search than a market survey or software requirements document.
- In class, students lead informal discussions on design and implementation. This leads to active participation in the learning process. These discussions facilitate inquiry-based learning (as opposed to teacher centric learning), a core component of PBL.
- Weekly sprints replace weekly sub-goals. Changes happen freely as students take ownership of the project.

In both models, students work with each other contributing their unique skills. However, the PBL refactored senior project course includes peer-review assignments to gauge the quality of collaboration. Presentations and writing assignments are still required (due to assessment), but also includes grades based on collaboration, and quality of the final product.

Specific to this work, the students identified some other works that automated core analysis, and wanted to develop an app that could be used by the industry. A few presentations are required, but most of the time in class was spent meeting one-on-one with the instructor. Meetings were loosely based on the Scrum project management framework where the students led discussions and identified barriers. The meetings were often short (following the Scrum meeting style) and the instructor would later address impediments to the team over office-hours, personal messenger (Discord) or e-mail.

Machine learning projects require powerful GPU compute servers. Specifically, they require NVIDIA graphics cards due to support for CUDA. Alternatives such as AMD/OpenCL are not cross-compatible with CUDA at time of writing. Grant support purchased a server with a NVIDIA Tesla V100S GPU. Students interfaced with the server using a terminal and SSH. Experiments were carried out using Python with TensorFlow and Keras libraries. From the perspective of offering this service to senior project capstone experiences we are skeptical that cloud services, such as AWS, would offer a satisfactory service to students. Cloud services charge per compute unit, and the experiments conducted in this work ran for days. Students would have to front this cost, which may be hundreds of dollars per project. For other departments planning to host machine learning-based capstone experiences we believe it is important for universities to maintain physical infrastructure to avoid pushing the cost onto students. The cost of these servers is of the magnitude where grant-support is required.

III.B. Project Management Strategies

Our industrial partnerships stemmed from one of our project members professional relationships. He has a background in geology (BS and MS Geology) and is currently pursuing a second bachelor's in computer science, while being employed full-time in the oil and gas industry. Throughout his time in the industry, he has made several connections that have been integral to the data collection part of the project. By leveraging these relationships, he managed to arrange meetings with technical and management staff at several different companies. Our first partner was one of the largest oil and gas producers in California, but because neural networks are very data intensive, we knew from the start we wanted to partner with as many companies as possible to collect a large inventory of data. To get our first partner to cooperate, we first met with the petrophysical staff to discuss the project and its merit. After being approved by the petrophysical staff, the project was presented to and discussed this with the management of an asset team. Subsequently, the project was discussed with the vice president of subsurface operations, who gave his full support in helping with the project in any way possible and granted full data permissions. Thereafter the same process was repeated with other oil and gas producers, who also decided to grant us permission to their data. It is important to note that it would be extremely difficult for any one individual to carry out an experiment of this type, as core analysis jobs typically range in the hundreds of thousands of dollars, and as previously mentioned, plenty of data is required for a successful implementation. In the same manner, it would be extremely difficult for anyone without the proper relationships and technical background to get the cooperation of oil and gas producers, as they are very protective of all core related data.

For the most part, our group member with the background in geology has been involved in doing outreach for the project as well as configuring the technical specifications, while the second group member has been involved in building the software and contributing new software related ideas.

III.C. Algorithms

CNNs were used as early as the 1990's to automatically detect handwriting on checks [12]. CNNs are an iteration of artificial neural networks also called "backpropagation neural networks" [13]. CNNs use "convolutional layers" that apply matrices (filters) of different values called "weights" onto an image using a convolution operation. It is speculated that earlier layers in the neural network can identify low-level features such as edge gradients. With every new layer added, the idea is that it will detect more complicated figures in the image such as shape, textures, objects, and other patterns. Neural networks are forward propagating, with their most common training method being the highly effective and efficient backpropagation algorithm.

Forward propagation involves passing pixel intensities from the input image through the network to the output layer to make a prediction.

Based on the correctness of the prediction, backpropagation calculates the "error gradient" and applies it backward to fine-tune the weights. A variation of the gradient descent algorithm is applied to calculate the prediction error with respect to the weights [14]. Because these operations involve high-cost linear algebra calculations over a set of input images, they are often performed using the rasterization pipeline of a GPU to speed up training time.

As the number of layers increases in a neural network, there is a phenomenon where the gradient diminishes to a near zero, reducing the trainability of the network. The problem of training deep networks was resolved with the addition of a new neural network layer known as "the residual block" [15]. In traditional neural networks, each layer feeds into the next layer. However, in a network with a residual block, every layer feeds into the next layer, and to the layers 2-3 layers away. It is a sort of bypass. The authors of ResNet claim it outperforms shallower networks without a vanishing gradient. ResNet is one of the most popular neural network architectures with over 20,000 citations. Before ResNet, it was thought that adding more layers was detrimental to performance. He et al. [16] shows that there exists a threshold for depth with the traditional CNN model.

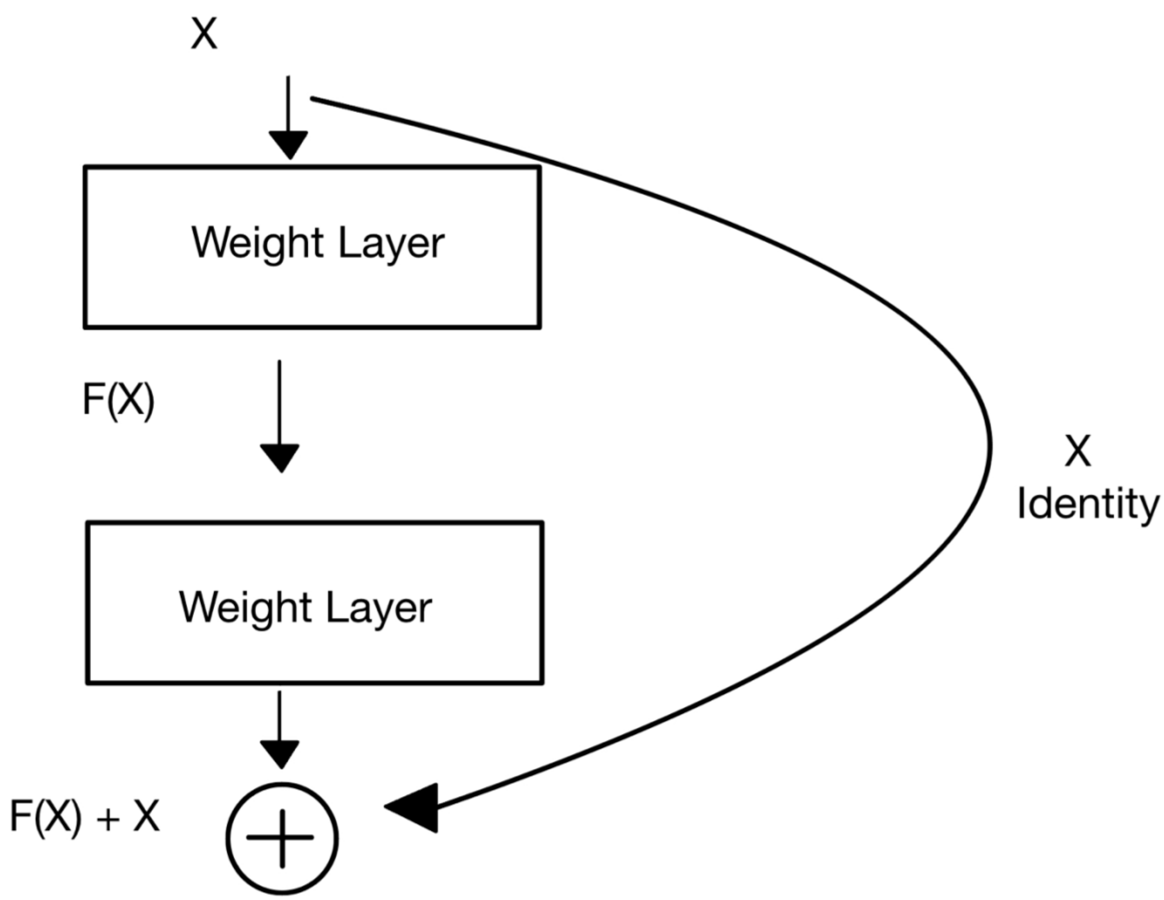

Figure 2. A residual learning block.

An alternative CNN architecture is the densely-connected-convolutional network or Densenet. Whereas Resnet takes the output of a previous layer as an input for a succeeding layer, with Densenet the input to the next layer is the concatenation of all the previous layer inputs (see figure 1 below) [17]. A compelling advantage of Densenets is that they require less computation than their counterparts. As stated by Huang et al. [17], “A Densenet that requires as much computation as a ResNet-50 performs on par with a ResNet-101.” Meaning Densenet only requires the level of computation a Resnet of 50 layers, while performing at the level of a Resnet of 101 layers.

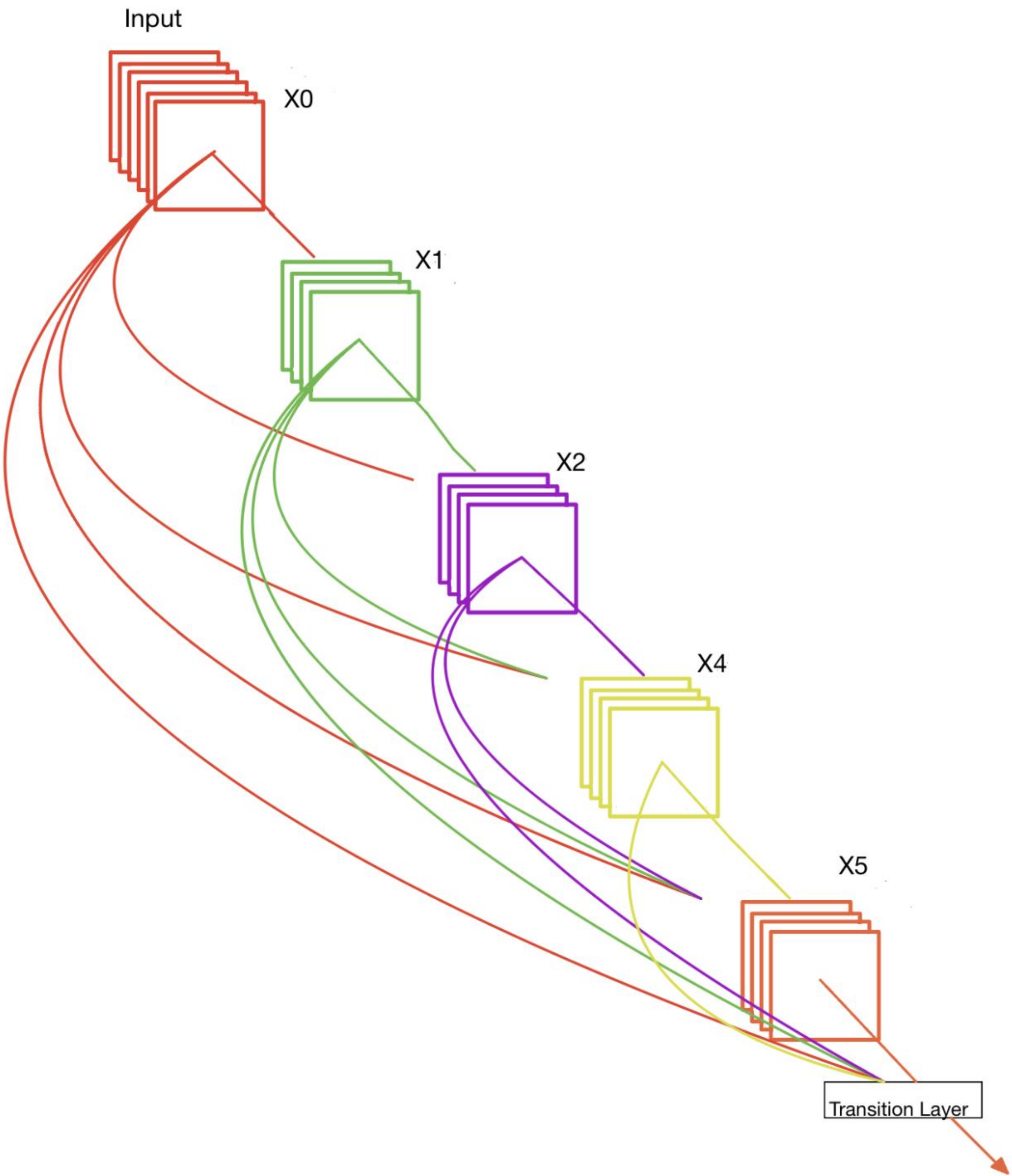

Figure 3. Each layer takes all preceding layers input.

VGG-19 is a standard CNN that uses very small convolution filters [18]. Because of the small convolution filters, it is not the fastest algorithm, as it takes longer to traverse through images. VGG is short for Visual Geometry Group, while 19 refers to the number of weight layers in the network.

In 2014, Google engineers published a paper introducing the Inception neural network architecture. This architecture was named after an internet meme, based on the 2010 Christopher Nolan film “Inception”. The concept of dreams within dreams was the central premise of the movie. The distinguishing feature of Inception is the improved use of computing resources inside the network through embedding of inception modules [19].

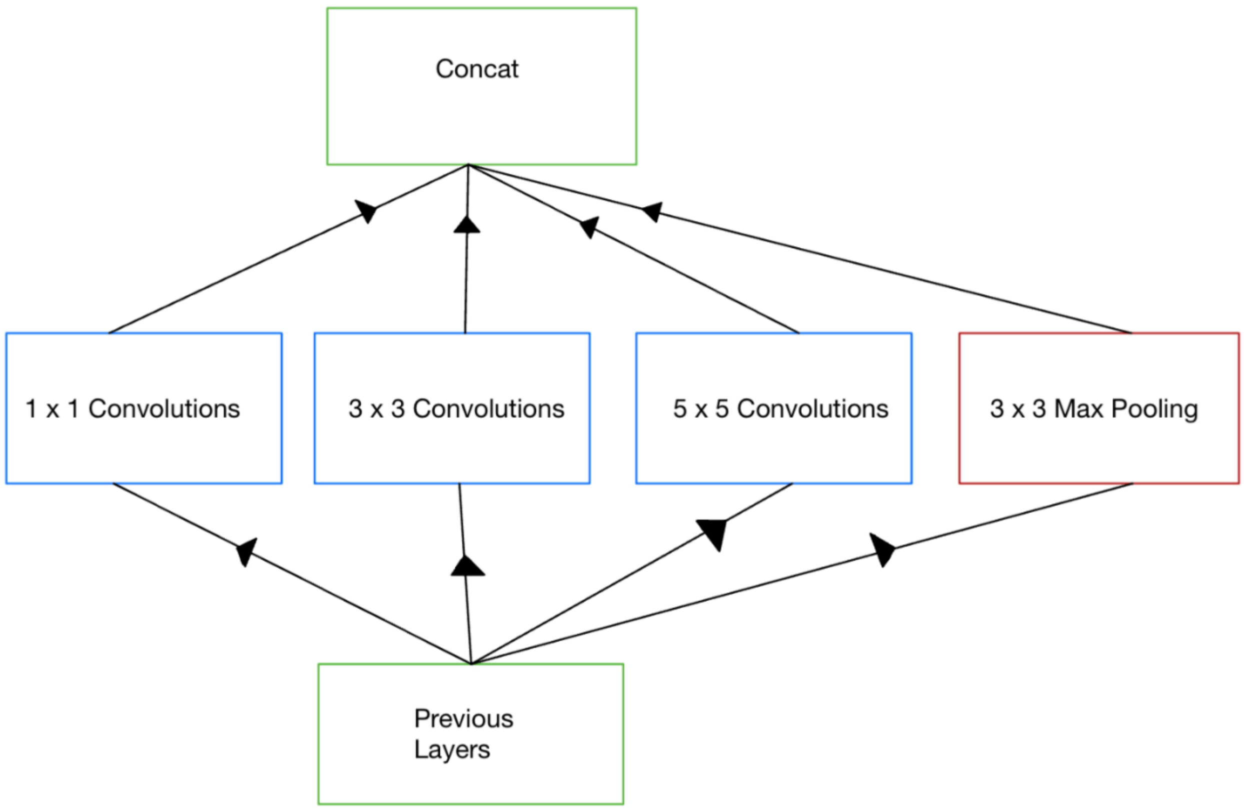

Figure 4. An inception module

Xception is known as an “extreme” version of Inception. The difference is the use of a depthwise separable convolution (a depthwise convolution followed by a pointwise convolution). A pointwise convolution is a convolution that uses the smallest possible filter, 1x1, effectively iterating through every single point of input. In short, Xception is a stack of depthwise separable convolution layers with residual connections. Xception outperforms Inception in accuracy and run time [20].

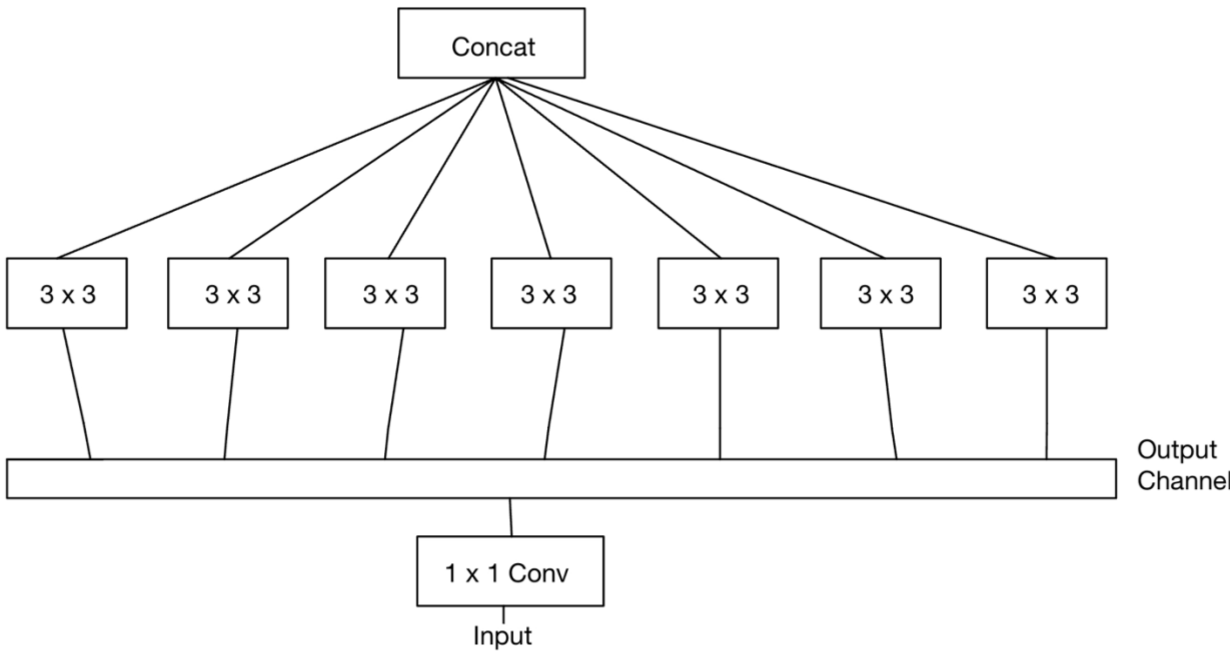

Figure 5. An extreme version of the Inception module, with one spatial convolution per output channel of the 1x1 convolution.

III.D. Workflow

When new data is obtained, we carefully review everything to see how we can incorporate it into the project. If both the images are of adequate resolution and the lab analysis work is available, we then incorporate the data into our samples for training the neural networks.

Approaching this data intensive project came with many challenges. Attaining the correct data was the first. Formatting and preparing the data was the second. Our core slabs were photographed in high resolution with white light and ultraviolet light to expose lithology and hydrocarbon (oil and gas) fluorescence. The core images were accompanied with a data report corresponding to analysis done at various depths, and included sample number, depth, porosity percentage, oil saturation, water saturation, oil to water ratio, grain density and a short lithologic description. Considering that we obtained sufficient data to work with, the challenge now rested in how to format and crop the images from each well using a python script. There is a general saying in artificial intelligence, garbage in, garbage out. We had to ensure that the cropped sections of the core were to the exact depth values in the data reports. This was especially challenging because the core slab images came in many different formats.

Core analysis in a lab is done with core plugs. Core plugs are one inch in diameter sections that are removed from the half of the core not used for imaging. To train the neural network with the data from core analysis, we had to create these core plugs from the core slab images. Our script iterated through the entire core slabs until it found a core plug location by referencing the data reports, it then created an image that represented a core plug, later to be fed to the neural networks.

Cropped images were separated into three categories based on oil saturation. High (greater than 20% oil saturation), medium (between 20% and 10% oil saturation) and low (less than 10% oil saturation). To ensure accuracy and avoid errors, we developed a script to automatically categorize the images. While creating the cropped images using the automated script, it would at the same time tag the name of the file with the oil saturation. This ensured that the images were categorized correctly. 40 samples were omitted for later testing and demonstrations. Once all images were labeled, the neural network training started with white and ultraviolet training happening separately.

All neural network code used for our project will be posted here.

IV. Results

Our experiments revealed that the neural networks achieved higher accuracy when trained on images taken under ultraviolet conditions, which was expected given that hydrocarbons fluoresce. Interestingly, both the white and ultraviolet trained neural networks outperformed a trained human. We evaluated performance using training accuracy, which measures how well the model learns over successive epochs, and testing accuracy, which measures performance on previously unseen images. Loss is the difference between the target and predicted outputs from the neural network. When trained on ultraviolet images, ResNet and Inception performed equally well, while Densenet achieved better performance with white light images.

	Training Accuracy	Testing Accuracy	Training Loss	Testing Loss
Densenet	0.9845	0.8542	0.0478	1.9525
ResNet	0.9845	0.8611	0.0437	3.4595
Inception	0.9775	0.8611	0.0711	0.9751
Xception	0.9706	0.8542	0.0855	2.2708
VGG19	0.9758	0.8264	0.054	2.3123

Figure 6. Results of all five neural networks at 2000 epochs (ultraviolet images).

	Training Accuracy	Testing Accuracy	Training Loss	Testing Loss
Densenet	0.9578	0.8176	0.1035	2.3396
ResNet	0.9563	0.7736	0.0774	2.5052
Inception	0.9547	0.7987	0.1332	1.1175
Xception	0.9641	0.7799	0.0936	1.2903
VGG19	0.9594	0.7736	0.0828	2.9203

Figure 7. Results of all five neural networks at 2000 epochs (white light images).

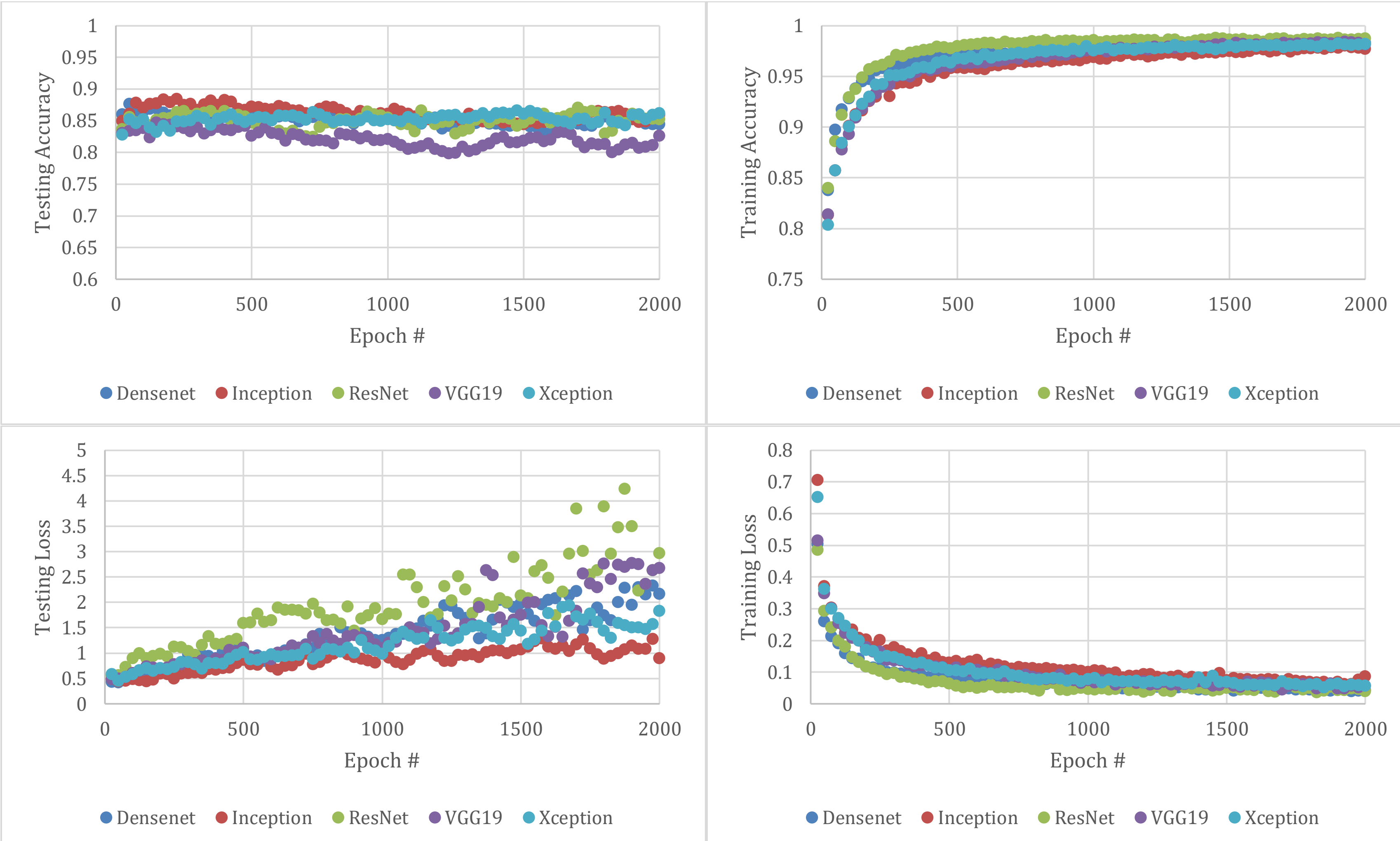

Figure 8: Plots of all five neural networks outputs with progressing epochs (ultraviolet images).

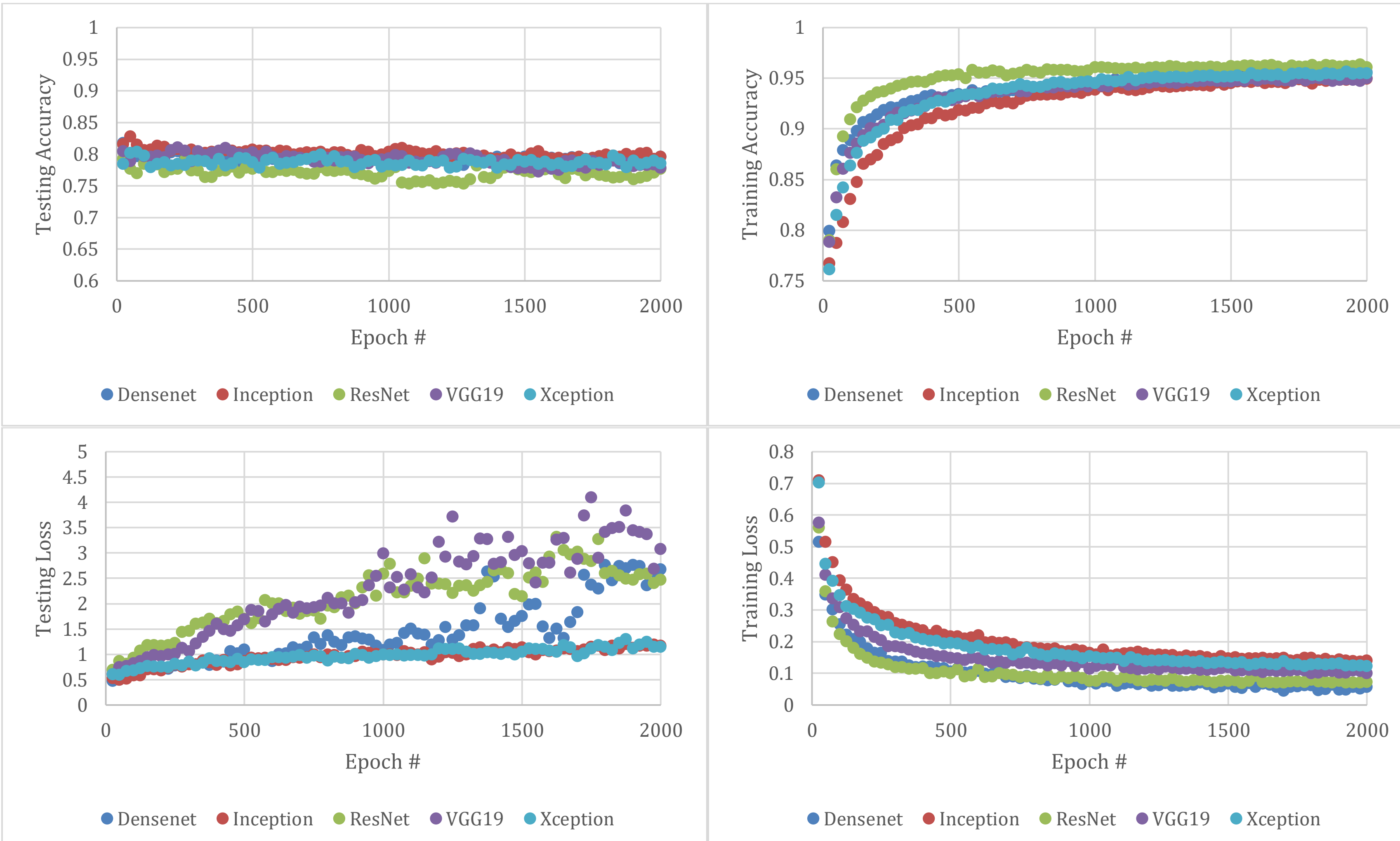

Figure 9: Plots of all five neural networks outputs with progressing epochs (white light images).

V. Conclusion

Oil and gas have proven to be an excellent energy source as they are naturally abundant, extremely reliable, and highly energy dense. The use of oil and gas since the industrial revolution has led to unprecedented economic growth, dramatically increased average life expectancy, and population growth [21]. The International Energy Agency reports that in 2022, about 80% of the world's energy was supplied by fossil fuels [22]. It is therefore in our best interest to improve the technologies used to find and extract oil and gas, while we transition to new energy sources. There is a growing number of applications for machine learning in the oil and gas industry including exploration, reservoir, drilling, and production [23] [24], and through this work we look to contribute to that movement. The results of our work up to this point are promising. We trained and tested five state-of-the-art CNNs, ResNet, Densenet, Inception, Xception, and VGG19, to detect oil saturation in core slab images with an NVIDIA Tesla V100S GPU. The average testing accuracy using ultraviolet light images was 85%, and 78% using white light images. With the neural networks now trained, the functionality of categorizing high, medium, and low saturations can be extended to all core slab sections that have been photographed in either white or ultraviolet lighting conditions, or both. Additionally, we provide guidance for other senior project/capstone instructors to create more meaningful senior project experiences using project-based learning (PBL). Future work will involve using these same neural networks to perform regression. More specifically, we look to generate oil saturation percentage values from the core slab images as well as automated lithology descriptions. With the support of university faculty and our partner companies, we are hopeful we can deliver quality results.

VI. Acknowledgement

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