Enhancing the performance of seismic fault detection using Convolutional Neural Network

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Abstract:

Seismic data plays a critical role in characterizing hydrocarbon reservoirs during the exploration stage, but the process of modeling geological prospects by interpreting seismic data can be laborious and time-consuming. Seismic surveys are key to oil and gas exploration, both onshore and offshore. Deep learning methods, such as convolutional neural networks (CNNs), have the potential to reduce the time and resources required for interpreting seismic data, ultimately lowering exploration costs, and enabling the discovery of previously undiscovered reserves.

Geophysical surveying procedures can be broken down into two key stages: seismic data collection and interpretation. Seismic waves that travel through the Earth are recorded using energy sources and an array of sensors. The collected data is then analyzed and prepared for seismic interpretation. One critical component of interpretation is detecting faults, as these can block or drain fluids in a reservoir. In the traditional approach, faults are detected as reflection discontinuities or abruptions, and manually tracked in post-stack seismic data, which can be tedious and time-consuming.

To increase efficiency, several automatic fault detection approaches have been proposed, with deep learning-based methods gaining the most attention. However, current methods often require large, labeled datasets to train the model, which can be prohibitive for smaller organizations that struggle to gather enough data. To address this issue, we employed a transfer learning technique that enables the use of smaller training datasets for automatic fault detection. We began by training a deep neural network on synthetic seismic data and retrained it using real seismic data. To gather real seismic samples and automatically produce appropriate labels, we used a random sample consensus (RANSAC) technique. We then demonstrated how retraining the network with a modest number of real seismic samples can significantly enhance the pre-trained network models' fault identification accuracy using three real-world 3D instances.

Introduction

A seismic survey is conducted to explore an area of interest using a technique called reflected seismology. This approach involves using an energy source to send a signal or wave into the subsurface, which interacts with the rock layers at different speeds and can reflect, refract, or diffract in various ways depending on their physical properties. The reflected waves are then detected by geophones installed on the surface, and their travel time is recorded. Based on the analysis of this data, a seismic interpreter maps the geological faults.

Faults are geological structures that result from a combination of tectonic plate movement, gravity, and overpressure. They are essentially cracks or planes in the earth's crust along which pieces of rock can move. Faults can vary in size from a few meters to several kilometers and are significant for oil and gas development because they can act as natural traps for hydrocarbons, helping to concentrate them in specific areas. Fault mapping is a crucial step in the reservoir characterization process, which aims to provide a comprehensive understanding of the reservoir's internal architecture and aid in the calculation of key economic indicators. In addition to facilitating the discovery of hydrocarbons, fault mapping is essential for optimizing the production of oil and gas from reservoirs.

Traditional fault detection systems require a seismic interpreter to manually trace and label faults, which can be time-consuming and inefficient. It may take weeks or even months to label faults in a typical area of interest. Researchers have proposed various strategies to improve the efficiency of interpretation, but methods that rely on statistical models based on only a few physical features are limiting and not very effective in detecting faults. As faults cause discontinuities and abrupt changes, the most advanced detection systems now use machine learning and deep neural networks (DNNs) to provide fast and accurate fault detection results. Using machine learning and DNNs can significantly improve the efficiency and reliability of fault detection in seismic interpretation.

The convolutional neural network (CNN) is one of the most used deep neural networks for a variety of tasks. However, to train CNN effectively, we need many labeled samples, which can range from thousands to millions. Collecting seismic data can be extremely expensive, making it difficult for smaller enterprises in the field to acquire large datasets to work with. The precise location of faults based on limited seismic data is crucial as it directly impacts exploration costs. To address this issue, our research employs a novel approach that utilizes synthetic data and a small sample of real data to train a U-Net-based CNN for automatic fault detection. With this approach, a seismic interpreter only needs to provide a few labeled samples to train the network, enabling the model to automatically detect and classify the remaining faults in the dataset.

Business Problem

The upstream expenses for oil and gas companies can be categorized into three main areas: 1- Acquisition, 2- Exploration, development and construction 3-Production and. Property acquisition costs relate to the purchase of proven and unproven oil and gas reserves. Exploration and development costs involve the expenses incurred in the search for new oil and gas fields, and the construction of facilities and infrastructure required to extract and produce reserves. Production expenses encompass the costs associated with the actual production of oil and gas from the field once it has been developed, including labor, equipment maintenance, and operating costs.

According to the US Energy Information Administration from Fig-1, exploration and drilling expenses are a significant component of annual expenditures for oil and gas companies. These costs include seismic surveys, drilling, and well-completion expenses, which can be substantial. In addition, property acquisition costs can also be a significant factor, particularly in areas with high potential reserves.

Overall, the upstream expenses for oil and gas companies can be substantial, and finding ways to reduce costs without sacrificing quality is critical for success in the industry. Effective exploration techniques, efficient drilling and production processes, and careful management of property acquisition costs are all key factors that can impact the bottom line for oil and gas companies.

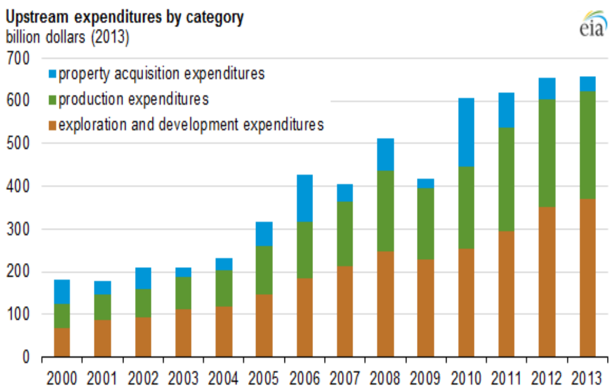

Fig-1

Cost reduction measures are crucial for oil and gas producers as they can significantly enhance profitability. Our proposed model for automatic fault detection using deep learning has the potential to provide several economic benefits, including:

• **Significant labor and time savings.** The traditional approach to mapping a common dataset using seismic interpreters can take several weeks or even months. However, by adopting convolutional neural networks (CNNs), this process can be completed in a matter of days with the only cost being the utilization of processing resources. This can significantly reduce the time and resources required for seismic interpretation, resulting in increased efficiency and cost savings for exploration companies.

Increased efficiency: The automatic detection of faults using deep learning techniques can reduce the time and resources required for interpretation. This, in turn, can increase efficiency and productivity, resulting in faster decision-making and reduced costs.

Enhanced accuracy: The use of deep learning-based fault detection techniques can significantly enhance the accuracy of fault identification. This can aid in the discovery of previously undiscovered reserves, leading to increased profitability.

• **Large datasets are not required**. The cost of acquiring large seismic datasets can be a significant expense for oil and gas companies. For instance, 3D mapping can cost between $40,000 to $100,000 or more per square mile. Moreover, purchasing large databases can also be costly. However, our proposed model for automatic fault detection based on CNNs requires only a small number of labeled samples for training, resulting in significant cost savings compared to traditional DNNs that rely on large datasets. By reducing the amount of seismic data needed for training, our model has the potential to make seismic interpretation more accessible and affordable for smaller organizations in the field. This would enable these organizations to take advantage of deep learning methods like CNNs, without incurring the same costs as larger enterprises.

•**Studying larger prospects**. Adopting faster and more efficient exploration techniques, such as the automatic fault detection model based on CNNs that we propose, can enable oil and gas companies to cover more areas of exploration in a shorter period. This, in turn, increases the likelihood of discovering new reserves, which can create more economic value for the organization. The time and resources saved by using our model can be redirected towards exploration and development, accelerating the pace of the discovery and development of new reserves. Furthermore, by reducing exploration costs, companies can allocate more resources toward research and development, technology upgrades, and sustainability initiatives. By optimizing exploration processes, oil and gas companies can improve their competitiveness and long-term viability in the industry.

The mechanism of the suggested seismic fault identification strategy is then presented. Finally, towards the end of this report, we summarize our findings.

Literature Review

A seismic image is a structural snapshot of the Earth's subsurface taken at a certain point in time. A 'source' delivers a sound wave to the subsurface, which travels at different speeds through the earth's strata and is reflected, refracted, or diffracted along the way. We record and stack the waves reflected from different geological layers to form a 2D or 3D image in seismic imaging. Because the physical qualities of distinct geological layers differ, the waves are reflected at the interface between layers due to density contrast. There are different sorts of waves, but in imaging, P-waves (compressional waves) are the most important. The image below shows an example of seismic acquisition as well as the final image once all the waves have been collected.

Faults are geological formations that result from various physical processes, such as pressure, gravity, and plate tectonics, among others. They are essentially fractures or planes along which a block of rock can move. Faults can vary in size from just a few meters to several miles in length. The San Andreas Fault, also known as the Transform Fault, is one of the most prominent examples of strike-slip faulting, in which two blocks of rockslide past each other horizontally.

Significance of Fault Mapping in seismic data

Fault mapping plays a crucial role in seismic exploration as it helps determine the presence of oil and gas reservoirs in the subsurface. In the initial phase of exploration, two key factors are crucial:

- Faults may operate as conduits for hydrocarbon migration.
- It may aid in the trapping of oil in place.

Faults can impact the hydrodynamics of a reservoir by altering fluid permeability. Therefore, fault mapping is essential for making accurate economic evaluations of a potential oil or gas play. The presence of faults in the subsurface can also affect the mechanical engineering element of oilfield development. Faults can change the structural integrity of a reservoir, leading to potential risks during drilling operations. Consequently, it is important to map faults throughout the entire oil and gas development phase to ensure the safe and efficient extraction of hydrocarbons.

Correct fault diagnosis is essential in the drilling process as it enables drilling bits to be directed to avoid faulty zones as much as possible. By avoiding faults, drilling can be conducted more efficiently and safely, reducing the risk of accidents such as blowouts or wellbore instability. This can also minimize the need for costly remedial actions, such as sidetracking or wellbore stabilization, which can impact the overall economics of a well. Additionally, avoiding faulty zones can increase the likelihood of successful completion and production rates, leading to increased economic value for the organization. In addition to its applications in oil and gas exploration, large-scale fault mapping has broader implications for the study of regional geodynamic processes on Earth. By analyzing fault patterns and their interactions, scientists can gain insights into the forces that shape the Earth's crust and contribute to natural hazards such as earthquakes, volcanic eruptions, and landslides. Accurate fault mapping can aid in the development of models that predict the likelihood and severity of these hazards, enabling better preparedness and risk management. Thus, fault mapping has important implications not only for the oil and gas industry but also for broader scientific research and societal applications.

As we can see, fault detection has various advantages, notably in hydrocarbon exploration. As a result, much effort has been put into a seismic investigation to precisely identify and map the faults. Manual mapping of faults, on the other hand, is a time-consuming operation that, even in a small survey region, can take days or weeks.

Data

Deep Neural Network (DNN) advancements have made it possible to train seismic images to construct a model that can locate flaws in seismic data. We will walk you through a Deep Learning Framework that can forecast faults using seismic data in the article. DNN advancements may make it possible to train seismic images to construct a model that can locate flaws in seismic data. We used synthetic seismic data provided by Force Competition for this project. Geoscience Australia has provided the Ichthys Seismic dataset, which can be accessed under a CC BY 4.0 license. The dataset showcases a polygonal fault system in the overburden that is well-defined. In the eastern portion of the survey, this fault system intersects larger planar faults. Additionally, the Jurassic section exhibits more diffuse fault zones that can still be identified by humans. The goal is to utilize a synthetic model trained algorithm that can accurately map shallow and deep faulting and closely resemble human interpretation.

Data Exploration

The data used in this study is in the SEG-Y format, which is the standard data format for seismic data in the industry (SEG stands for Society of Exploration Geophysicists). This is a specialized format, and we utilized a Python library named 'segyio' specifically designed for reading this format. Since we were working with a 3D dataset, the segyio library easily converted it into a 3D NumPy array. An example of a 3D grid structure is illustrated in Fig-2, featuring three planar surfaces: inline, crossline, and z-slice. These 2D surfaces are widely used in the seismic industry to visualize data.

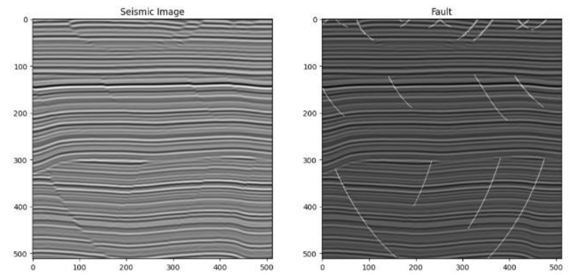

Fig-2

Methodology

The project utilized a Convolutional Neural Network (CNN) to analyze 3D Seismic images efficiently through specific convolution and pooling operations. The objective was to accomplish a fault mapping task, which involves image segmentation. To achieve this, the U-Net++ framework was chosen since the desired outcome is a high-resolution image.

The U-Net++ architecture comprises two distinct paths:

(i) The first path, known as the U-Net++ encoder section, involves multiple down-sampling steps. This section includes two 3x3 convolutions, a Rectified Linear Unit (ReLU) activation function, a 2x2 max pooling operation, and a stride of 2 for downsampling. The encoder section also includes nested U-Net architectures that allow the model to capture features at multiple scales.

(ii) The second path, referred to as the U-Net++ decoder section, involves multiple upsampling steps. This section comprises an up-sampling operation to increase the feature map size, a 3x3 convolution, and concatenation of the previous contracting block's feature map. Subsequently, three 3x3 convolutions with ReLU activation are performed. The decoder section also includes nested U-Net architectures and skip connections that help to preserve the spatial information lost during the encoding path.

The original U-Net implementation generates an output shape smaller than the input, requiring a skip connection layer size that corresponds to the current layer. To match the size of the layer after the final U-Net block consists of four contraction and four expansion blocks, along with a feature map block at the network's start and end. upsampling and convolution, the skip connection layer needs to be cropped. Additionally, setting the padding to 1 ensures the final output shape matches the input shape. Finally, a final code block is required to produce tensors of the same input size.

The final U-Net++ block consists of four contraction and four expansion blocks, along with a feature map block at the network's start and end.

Training Data

In this study, we worked with two data volumes: a seismic cube and a fault cube. The seismic cube will serve as the training data, while the fault cube served as the label data. The fault data consists of surfaces that have been manually mapped and have values between 0 and 1. From Fig-3, The left image displays a 2D seismic display in the inline direction, while the right image displays the same display with faults overlaid.

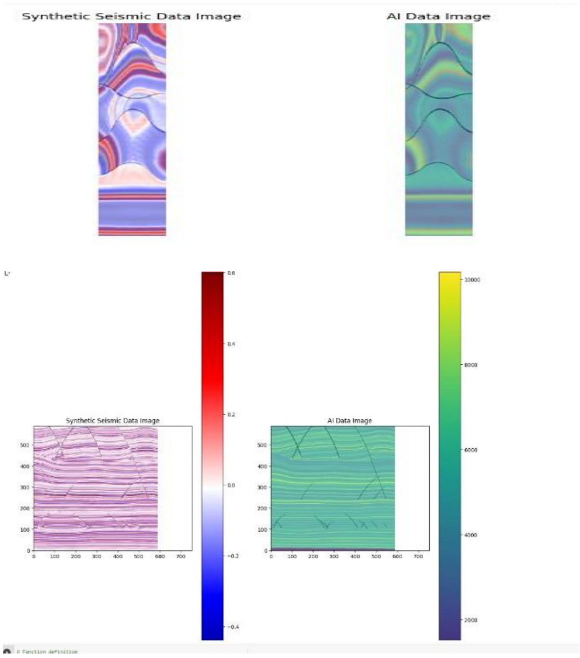

Fig-3

The original input data has a shape of (101, 589, 751), with 101 inlines, 589 crosslines, and a total of 751 samples. As the seismic images are grayscale and not RGB, they can be considered single-channel grayscale images. The batch size can be determined from the number of inlines, and each inline corresponds to a 2D image with dimensions of 589 x 751 pixels. To fit the desired input tensor shape of (batch size, channels, height, width), we represent our input tensors as (101, 1, 589, 751), where 1 denotes a single channel. However, due to some issues with the odd size, the input volume was cropped to obtain a shape of (101, 1, 512, 512).

Model Training

These are the general training parameters: the model was trained for 20 & 35 epochs, although we noticed that the model becomes proficient at identifying faults after about 5 epochs. We executed the training process one batch at a time on a Google Collab with GPU 0: Tesla T4, NVIDIA-SMI equipped with 12GB of memory.

Result

The pictures shown were randomly collected during three different time periods. By Epoch 4, the model has started identifying defects and by Epoch 10 it has managed to accurately pinpoint the fault.

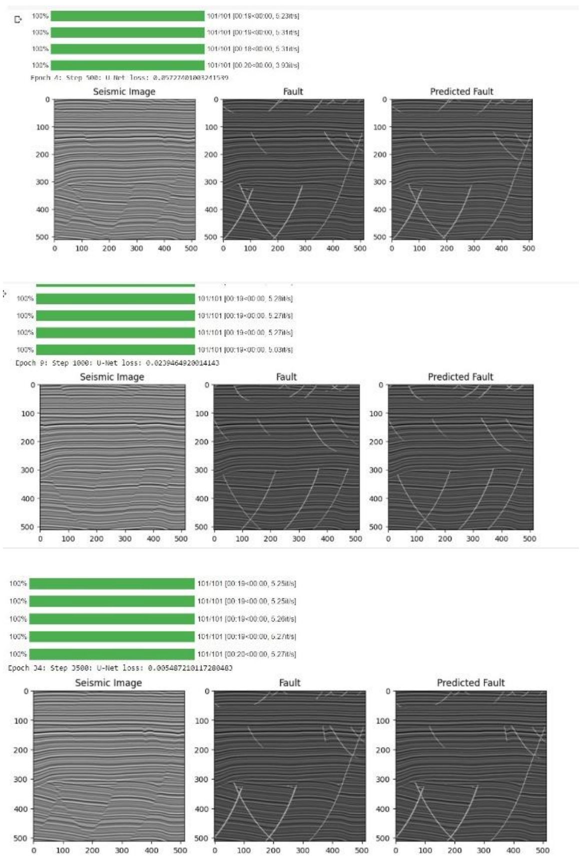

Fig-5

Examining the model's efficiency, we can observe a significant drop in the loss function in the initial 5 epochs, followed by a plateau around the 15th epoch. This speedy decline in the model's loss is probably attributed to the incorporation of pristine synthetic data during training.

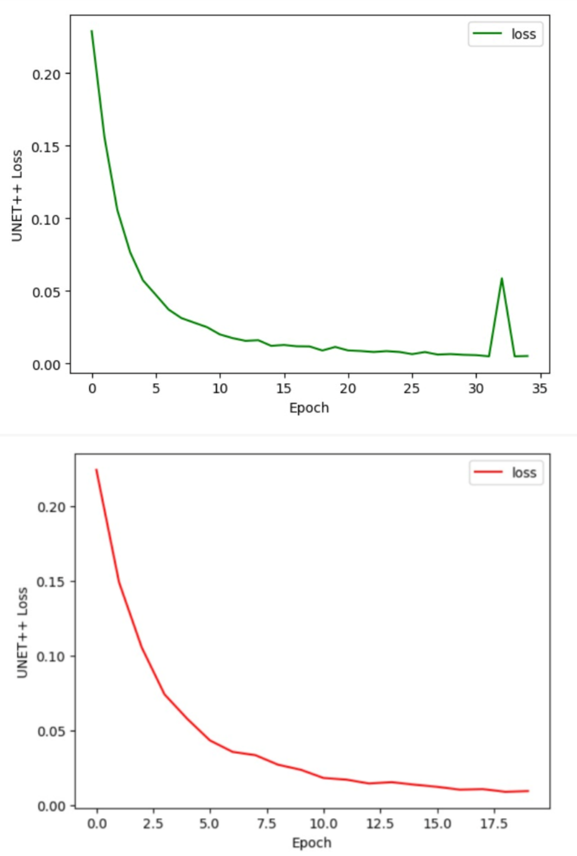

Fig-6

Conclusion

The results of our project demonstrate the effectiveness of our proposed CNN method in swiftly identifying faults, given that the input data is free of noise. However, in real-world scenarios, seismic data is often highly distorted and full of interference, which can significantly impact the accuracy of the model. Nevertheless, by training the model with a diverse range of seismic datasets from various basins around the world, it can develop robust generalization skills. This highlights the potential of deep learning in fault detection, even with complex and noisy data, as long as the model is trained with a broad range of input data.

Acknowledgment

This project was a collaborative effort, and we could not have completed it without the support and assistance of many individuals. We would like to express our sincere gratitude to Dr. Mohamad Ibrahim Mohamed for providing us with guidance, constant supervision, and valuable insights throughout the project. His willingness to share their extensive knowledge enabled us to comprehend the project thoroughly and complete the assigned tasks on time. We would also like to extend our thanks to Geoscience Australia for providing us with invaluable data for research purposes. Their contribution was instrumental in the success of this project, and we are deeply grateful for their support. Finally, we would like to thank our team members for their hard work and dedication throughout the project. Their collaboration and commitment were essential in achieving our goals.

Nomenclature

- **CNN:** Convolutional Neural Network
- **Architecture:** U-Net++
- **SEG-Y:** Society of Exploration Geophysicists
- **Planar surfaces**: inline, crossline & z-slice
- **ReLU:** Rectified Linear Activation Unit
- **Concatenation:** Increases the precision of learning

Reference

1. https://doi.org/10.3390/en14123650
2. https://doi.org/10.1093/jge/gxy015
3. https://doi.org/10.1016/j.cageo.2021.104776
4. http://www.xeek.ai
5. https://github.com/bolgebrygg/Force-2020-Machine-Learning-competition/tree/master/fault_mapping_competition
6. https://www.evaluateenergy.com
7. https://nextcloud.drgaff.net/index.php/s/7mXn8mSbjxdZyr8
8. Van Bemmel, P.P.; Pepper, R.E. Seismic Signal Processing Method, and Apparatus for Generating a Cube of Varianc Values. U.S. Patent 6,151,555, 21 November 2000. 5.
9. Di, H.; Gao, D., Efficient volumetric extraction of most positive/negative curvature and flexure for fracture characterization from 3d seismic data. Geophysical Prospecting, Nov. 2016, DOI:10.1111/1365-2478.12350
10. Aqrawi, A.A.; Boe, T.H. Improved Fault Segmentation Using a Dip Guided and Modified 3D Sobel Filter; SEG Expanded Abstracts: San Antonio, TX, USA, 2011; pp. 999–1003.
11. Araya-Polo, M.; Dahlke, T.; Frogner, C.; Zhang, C.; Poggio, T.; Hohl, D. Automated fault detection without seismic processing. The Lead Edge 2017, DOI:10.1190/tle36030208.1

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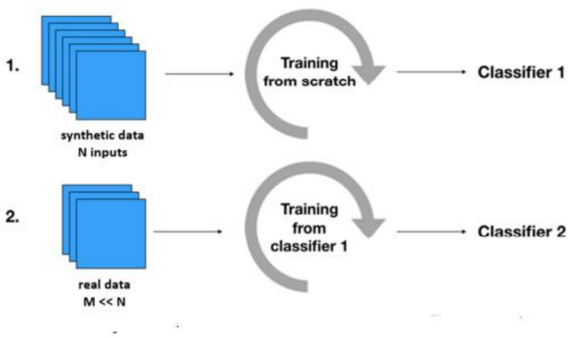
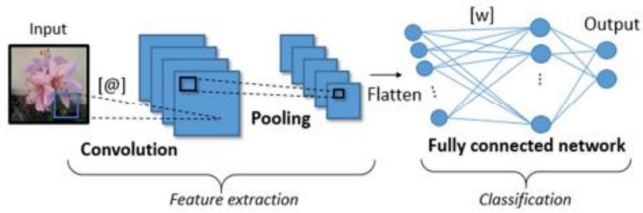
Appendix



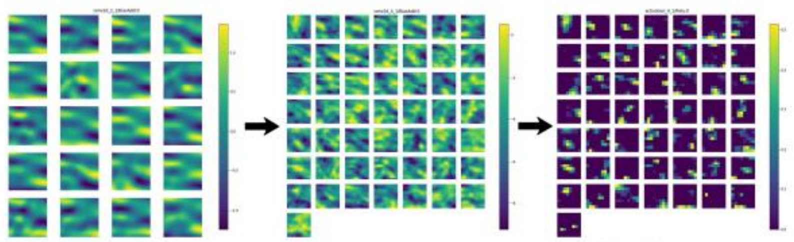
Workflow



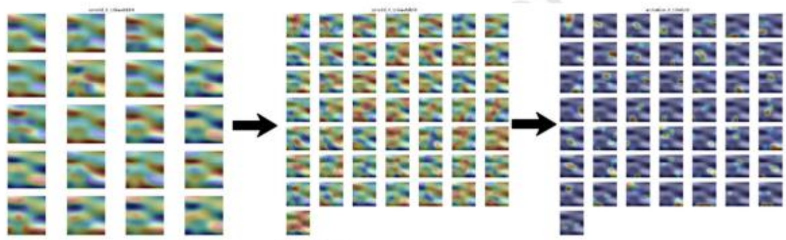
. Architecture of a CNN, with: [@] = trainable filters; [w] = trainable weights.

CNN Architecture

Transfer learning strategies



CNN feature map of two convolution layers and activation layer highlighting learned features.



. CNN heatmap of two convolution layers and activation layer highlighting learned features.

Transfer Learning Procedure