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Deep Learning Approaches To Image Classification: Exploring The Future Of Visual Data Analysis

Manikanth Sarisa[1*], Venkata Nagesh Boddapati[2], Gagan Kumar Patra[3], Chandrababu Kuraku[4], Siddharth Konkimalla[5]

[1*]Prin. Software Eng. Ally Fin. Inc, manikanthsarisa@outlook.com
[2]Microsoft Support Escalation Engineer, venkatanageshboddapati@yahoo.com
[3]Tata Consult. Serv. Sr. Solution Arch, gagankumarpatra12@outlook.com
[4]Mitaja Corporation Sr. Solution Architect, ChandrababuKuraku@outlook.com
[5]Amazon Com LLC Network Dev Engineer, SiddharthKonkimalla@outlook.com

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ABSTRACT

Over the past decade, deep learning has emerged as a revolutionary technology for the analysis of visual data, particularly images. This master's thesis focuses on deep learning approaches to image classification, which is a key task in many applications using visual data analysis. A state-of-the-art deep learning model, namely the Vision Transformer (ViT), is explored for image classification. ViT is trained using transfer-learning techniques on a new dataset of over 350,000 photographs of European buildings in eight cities, obtained across two separate flights from a drone-mounted camera. Initial results demonstrate that models pre-trained on large datasets such as JFT-300M can achieve performance competitively with the fine-tuning of models trained from scratch on smaller datasets and that ViT outperforms convolutional neural networks for drone-captured images. Further, the prospects of deep learning for image classification are discussed, highlighting the potential impact of new research directions within the architectural vision transformer domain (e.g., Swin-Transformer, CrossViTs, T2T-vision Transformer) and new training techniques (e.g., Vision-Language Pre-training models, multi-modality input). The exponential increase in data generated by cameras, mobile devices, and Internet-of-Things (IoT) sensors has escalated the need for automated processing and analysis of visual data. Furthermore, images and video frames are a popular medium for data collection across various domains, including commercial and industrial. Image classification, or finding the most relevant label for a given photograph, is one key task in many applications using visual data analysis. Popular applications include multimedia search engines, mobile applications navigating to points of interest (POI), and anomaly detection in industrial cameras. As a consequence, many datasets have been assembled, containing millions of photographs collected and labeled according to city, object, or scene. Deep neural networks trained end-to-end directly on pixels have become state-of-the-art image classification technology. More recently, architectures based solely on attention mechanisms, eschewing convolutions, have challenged the long-standing dominance of convolutional neural networks.

Keywords: Deep Learning, Image Classification, Vision Transformer (ViT), Transfer-Learning, Drone- Captured Images, Convolutional Neural Networks, Attention Mechanisms, Multi-Modality Input, Architectural Vision Transformer, Dataset.

1. Introduction

As visual data becomes increasingly prevalent, the need for effective image classification techniques is a growing concern. Image classification refers to the process of categorizing images into different classes based on their content or features. This is a challenging task due to the inherent complexity and variability of images, such as changes in lighting, scale, orientation, and occlusions. In addition, images often contain redundant and irrelevant information, which can complicate the classification process. With the rise of social media platforms and the ubiquity of smartphones and cameras, there has been an exponential increase in the production of visual data. This has sparked advances in algorithms and systems for the analysis of images, videos, and other visual modalities, resulting in a once-dominant field for artificial intelligence (AI) technologies to achieve success. In conjunction with efforts to reduce the cost of data collection, storage, and processing, there is a need for the development of systems capable of classifying visual data with high accuracy and efficiency. Over the past two decades, there have been immense efforts devoted to building image analysis systems both in academia and industry. Traditional image classifiers generally operate on a two-step paradigm, where low-level features or descriptors are first extracted from images, followed by the use of classifiers relying on these extracted features. Feature extraction is a crucial step in image classification.

Conventional feature extraction techniques rely on handcrafted low-level descriptors to model the content or structure of images. These include color-based descriptors such as color moment and color histogram, texture-based descriptors such as Gabor wavelet and local binary pattern, and shape-based descriptors such as Hu moment and Fourier descriptor. Although these manually designed descriptors achieve satisfactory performance for many applications, there are several limitations. Such descriptors may not be able to describe the overall information of images due to their local characteristics. They also neglect the high-level concepts contained in images, such as objects and scenes. Moreover, the descriptive power and robustness against noise or occlusion of the handcrafted descriptors are usually limited. In recent years, deep learning models have emerged as a new kind of model to extract features automatically from images. Deep learning is a subfield of machine learning that comprises a family of models with multiple levels of abstraction. In visual data analysis, deep learning generally refers to the use of deep neural networks with more than five layers, which grew out of decades of work in various fields such as artificial neural networks (ANNs), computer vision, cognitive neuroscience, and information theory. Deep learning has many variants including deep fully connected neural networks (CNN), deep convolutional neural networks (CNN), deep belief networks (DBN), deep recurrent neural networks (RNN), deep Gaussian-based networks (DGN), and so on. Of these, DCNN is the most successful and well-known architecture, demonstrating unrivaled performance in various applications. The purpose of this research is to examine current deep-learning methods used for image classification. The following section presents a review of the literature on previous works related to the visual data analysis field, followed by a discussion of research objectives.

1.1. Background and Significance

In recent years, deep learning approaches have gained substantial attention and prominence in the fields of machine learning and computer vision. With the rapid proliferation and widespread adoption of smartphones, laptops, and cameras, the amount of visual data being generated is increasing at an exponential rate. According to a report, the visual data size has increased from 8PB in the year 2010 to more than 44ZB in 2020 and is expected to reach 175ZB by. In addition, the increase in the number of cameras installed worldwide has made it critical to analyze the visual data being generated. A surveillance camera generates 30GB of data every hour, and analyzing this data manually is extremely cumbersome and tedious. Therefore, automatic approaches to analyzing visual data are imperative to handle large-scale data and information. Image classification is one such task that aims to assign predefined class labels to given test images based on their visual contents. Search engines like Google, Yahoo, and MSN utilize image classification techniques to return images based on queried keywords.

Image classification has been an extensively researched theme in the field of computer vision for the last three decades. A variety of hand-crafted feature extraction approaches such as Scale Invariant Feature Transform (SIFT), Histogram of Oriented Gradients (HOG), and Color Histogram have been proposed, followed by their association with different classifiers like k-nearest neighbor (kNN), decision tree, and support vector machine (SVM). Combined, such approaches are known as traditional approaches or shallow methods. Even though traditional approaches provide good performance on small databases, their performance deteriorates on large-scale heterogeneous visual data. Good performance is not only a requirement but also a necessity for effective large-scale visual data analysis. Moreover, traditional approaches are also computationally expensive, and the required time increases with an increase in the size of the image data. Deep Convolutional Neural Network (CNN), a class of deep learning approaches, has gained much attention and has emerged as the state-of-the-art method for large-scale image classification. DCNNs are hierarchical multi-layer networks, composed of various layers like the convolutional layer, pooling layer, and fully connected layer. The end-to-end structure of DCNN allows automatic learning of representative feature maps from training images, and the utilization of several hidden layers enables capturing hierarchical semantics. Exploitation of spatial correlations, translation invariance, and local connectivity present in objects is achieved through the convolutional layer, making the architecture suited for visual data. In addition, deep models are capable of training on readily available high-performance Graphics Processing Units (GPUs), making fast learning of large-scale networks possible. With several advantages, a surge of interest in deep learning approaches for visual data analysis and understanding has been observed, and state-of-the-art performance has been demonstrated on several benchmarks.

1.2. Research Objectives

The primary objective of the research is to conduct a comprehensive review of current deep learning techniques applied to image classification and to identify potential areas for future investigation. This will involve an in-depth analysis of various algorithms, models, and architectures that have been successfully implemented for image classification tasks. Attention will be given to the strengths and weaknesses of each approach, as well as the challenges that remain to be addressed. A secondary objective of the research is to investigate a specific deep-learning approach to image classification and to implement it on a publicly available dataset. This will involve selecting a suitable dataset, preprocessing the data, and training a deep-learning model for image classification. The performance of the model will be evaluated and compared to that of other approaches, and the results will be discussed in the context of the broader research objectives.

2. Foundations of Deep Learning

Deep learning, as a subset of machine learning, interconnects artificial intelligence and data science. It implies the use of large datasets and processing by multiple layers of nodes (algorithms), which deal with and relate to characteristics, patterns, and other properties of the data. Networks are represented through an architecture formed by nodes (neurons) in which a semi-random model is generated. By applying a deep learning approach, the model can be improved through training based on the dataset, building the ability to extract useful insights from a given dataset. Neuroscience inspired the implementation of neural networks, aiming to model the brain's cognition by optimizing performance through a network of edges connecting processing nodes. Nodes are in charge of analyzing information by weighting and biasing its inputs, utilizing an activation function that assesses this value to define if it should be propagated to the following layers in the network. Gathering many edges and nodes forms a connected network which, in its shallowest form (one layer of nodes), can only classify data by linear combinations of inputs. Additionally, over the edges' weights and nodes' biases, there is a global bias applied to each layer that impacts all the nodes. Enhancing this basic architecture with additional connected layers increases the level of abstraction regarding the latent features of the data.

The architecture of deep learning networks can either be feed-forward or feedback. In feed-forward networks, information flows from the input layer, feeding it ahead in the network until a decision is output or a prediction is made. In feedback networks, information can also propagate back to prior layers, forming a closed loop that recurrently redistributes the information. Regardless of the architecture definition, network training can generally be separated into two categories: supervised learning and unsupervised learning. In supervised network learning, a labeled dataset is fed into the network for training, and the output is compared to the expected one. After that, adjustments are made to improve the resulting prediction. In unsupervised learning, no prior labels are needed for the data input during training. Still, clear expectations on the performance of the network or measured outputs are necessary after training. Thus, only the model is trained, permitting the inference of properties of the data using latent features as proxy inputs.

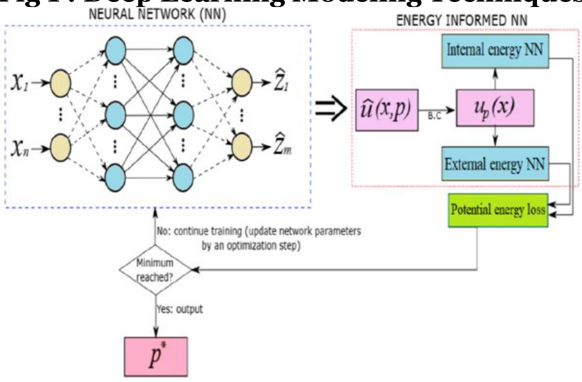
The interconnected edges of the network form a weight matrix that defines the distribution of data inside the network and the eventual learning of specific patterns taught by training. In this manner, weights are iteratively adjusted by the backpropagation algorithm that computes the gradient of the expected cost/junction (loss based on the difference between the expected class and the predicted one) concerning weights. The calculated gradients are subsequently employed to adjust the weights to minimize the loss function. There exists a variety of loss functions, whereby the one used is defined by the training problem and the underlying architecture. On the other hand, to mitigate the overfitting problem regarding a dataset used for training, different methods can improve network generalization capabilities. Emerging from the former scientific community, a subset is composed of model selection techniques. These include cross-validation, early stopping, weight decay, data augmentations, and dropout; more recently emerging dropout-type methods include freeze-out and repeat dropout. Alternatively, boosting and bagging are techniques used to involve multiple models without enforcing the models' properties.

2.1. Neural Networks

As one of the main architectures used in deep learning, neural networks have been a critical area of exploration across different research domains and industrial applications. Most neural networks used in the deep learning field are based on the idea of the artificial neuron proposed by McCulloch and Pitts in 1943. Artificial neurons mimic the behavior of biological neurons. These biological neurons receive inputs from dendrites, sum them, and produce an output spike through the axon if they surpass a firing threshold. A similar approach was proposed to design artificial perceptron neurons. Each artificial neuron has several inputs with associated weights, which are summed once multiplied by a step function.

Neurons were the initial basis for the design of neural architectures. Perceptrons are the simplest neural architectures, composed only of this simple neuron design. In perceptrons, inputs are fed into an interconnected layer of perceptron neurons, whose output can be linked to other further layers of perceptron neurons. The outputs of this architecture are binary. To use them efficiently and obtain an outcome, it is important to solve the first problem, which is the weights optimization. Initially, Rosenblatt presented the perceptron learning rule to limit the weights and construct a simple quadratic convergence function. However, this learning rule does not provide guaranteed convergence to the solution in many situations. Later on, Widrow and Hoff introduced the least mean square (LMS) approach based on the concept of image errors. They performed batch learning on this neural architecture. Convergence is guaranteed, which is a major advantage. A solution with more associated neurons and simple mathematical structures was needed to solve highly complex problems. This architecture was proposed by Nils Aall Barricelli in 1961. The architecture named "Multi-Layer Network" (MLN) consists of a perceptron connected to further hidden layers of perceptrons. To optimize the weights of a multi-layer architectural design, learning rules were required to decompose the task. A well-known backpropagation algorithm was inspired by the adjustable coefficients of multi-layer analog controlled systems proposed by Paul Horowitz. This multi-layer neural network is the architecture broadly employed in the deep learning field.

Fig 1 : Deep Learning Modeling Techniques



2.2. Convolutional Neural Networks (CNNs)

Convolutional neural networks (CNNs) emerged as a transformative architecture, significantly advancing the field of image classification. This model, a subtype of deep neural networks (DNNs), initially gained widespread attention after securing the top position in the ImageNet Large Scale Visual Recognition Competition in 2012. Its remarkable performance in targeting image classification tasks and its versatile design for application in various domains further enhanced its appeal. The essence of CNNs lies in their mimicked functionality of the human visual perception system. Their architecture mimics the layered structure of vision, comprising neurons organized in multiple layers and selectively responsive to various visual stimuli. CNNs capitalize on the spatial structure of images, leveraging local connectivity via convolutional filters to learn distinctive features. These learned features are then utilized as inputs for fully connected layers, which yield final classifications. CNNs exhibit high efficiency in handling image data, utilizing considerably fewer parameters than conventional neural networks.

An integral aspect of the CNN architecture is its hierarchy composed of three types of layers: convolutional, pooling, and fully connected. Convolutional layers can be viewed as sliding a window with learnable filter weights across an input or previous feature value map, where neurons in the section share the same weights. This learning process adapts the filter to extract certain features. The pooling layer, following the convolutional layer, randomly selects or averages a subset of values in a specific section of a feature map, enhancing robustness against input noise and variations in translation, rotation, or scale. Finally, the fully connected layer flattens all previously learned features into a one-dimensional vector. Neurons in this layer are connected to all inputs, forming an abstraction of the represented features and yielding the final classification. After the last layer, a non-linear activation function is applied to augment the model's expressiveness, with the softmax activation function widely employed for multi-class classification tasks. Training a CNN model involves optimizing its parameters to minimize a specific cost function through backpropagation and an optimization algorithm. Two essential characteristics of CNNs contribute to a reduced risk of overfitting during training: the weight sharing of neurons in a convolutional layer and the pooling operation. The weight sharing of neurons in a convolutional layer restricts the number of free parameters to optimize, significantly reducing the computational load, especially for images with large resolutions. Pooling layers further decrease the input to subsequent layers while retaining critical information, collectively enhancing robustness against input noise and lowering the dimensionality of the learned parameters.

2.3. Recurrent Neural Networks (RNNs)

As the field of deep learning continues to evolve, researchers are exploring new architectures and techniques to improve the performance and applicability of neural networks. One promising area of exploration is based on recurrent neural networks (RNNs), which are particularly effective for tasks involving sequential data. RNNs are a type of neural network architecture that is specifically designed to process sequential data. Unlike traditional feedforward neural networks, which treat each input independently, RNNs maintain a hidden state that is updated at each time step of the sequence. This hidden state serves as a memory of the past inputs, allowing the network to model temporal dependencies in the data. The basic architecture of an RNN consists of an input layer, a hidden layer with recurrent connections, and an output layer. The input layer receives a sequence of inputs, which are transformed by a weight matrix and passed to the hidden layer. The hidden layer applies a non-linear activation function to the weighted sum of its inputs, and the output is computed as a weighted sum of the hidden state. One of the key features of RNNs is their ability to process variable-length sequences. This is achieved by unrolling the network in time and treating each time step as a separate layer in a feedforward network. The weights of the network are shared across all time steps, which allows the network to generalize to sequences of different lengths. Because of this, RNNs can be applied to a wide range of tasks, including speech recognition, natural language processing, and video analysis. Despite their success in modeling sequential data, RNNs have some limitations. One of the main challenges is the vanishing and exploding gradient problem, which makes it difficult to train RNNs with long sequences. This problem arises because the gradients of the loss concerning the weights can become very small or very large as they are backpropagation through time.

To address these challenges, several variations of the basic RNN architecture have been proposed. One of the most popular variants is the long short-term memory (LSTM) network, which uses a more complex hidden state that includes input, output, and forget gates. These gates control the flow of information into and out of the cell state, allowing the network to store information for longer periods. This architecture has been shown to perform well on a variety of sequential tasks, including language modeling and speech recognition. Another effective approach to improving the performance of RNNs is to use attention mechanisms, which allow the network to selectively focus on specific parts of the input sequence. This helps the network deal with long sequences and capture important features that may be missed by vanilla RNNs. Attention mechanisms have been successfully applied to a wide range of tasks, such as image captioning and machine translation. In conclusion, RNNs are an elegant extension of standard feedforward neural networks for modeling sequential data. Since their inception, many variants such as LSTMs and GRUs have emerged to better combat the issues of training RNNs. More recently, attention mechanisms have further improved the performance of RNNs on information-heavy sequential tasks.

Recurrent Neural Networks (RNNs) represent a sophisticated advancement in neural network architectures designed to handle sequential data by maintaining a hidden state that captures temporal dependencies. Unlike traditional feedforward networks that process inputs independently, RNNs update their hidden state at each time step, enabling them to model sequences of variable lengths effectively. However, RNNs face challenges such as the vanishing and exploding gradient problems, which complicate training with long sequences. To overcome these issues, variants like Long Short-Term Memory (LSTM) networks have been developed, incorporating input, output, and forget gates to manage information flow and extend memory capabilities. Additionally, attention mechanisms have further enhanced RNN performance by allowing the model to focus selectively on different parts of the input sequence, improving its ability to handle complex tasks such as language modeling and machine translation. Together, these innovations have significantly advanced the utility and effectiveness of RNNs in processing sequential data.

Equation 1 : Gradient Descent Optimization

From the expression we derived earlier,

$$f(x+\alpha v) = f(x) + \alpha v \nabla_x f(x)$$

taking partial derivatives on both sides w.r.t α, we get

$$\begin{aligned} \partial f(x+\alpha v)/\partial \alpha &= 0 + v \nabla_x f(x) \\ &= v^T \nabla_x f(x) \\ &= \|v\| \|\nabla_x f(x)\| \cos\theta \\ &= \|\nabla_x f(x)\| \cos\theta \qquad \text{...as } \|v\| = 1 \end{aligned}$$

where θ is the angle between the gradient $\nabla_x f(x)$ and the unit vector v

3. Image Classification Techniques

Image classification, aiming to categorize images into predefined classes, is fundamental to computer vision. Conventional approaches like KNN, SVM, and MRF, while foundational, are often limited in performance. In contrast, deep learning, particularly CNNs, has revolutionized image classification. Traditionally, image classification relied on hand-engineered features like color histograms or edge maps. Classifiers like KNN, SVM, and MRF used these features. While effective for simple tasks, these methods struggled with diverse databases and complex scenes. With the rise of large datasets and powerful GPUs, research momentum shifted to more data-driven learning methods.

Deep learning took center stage in computer vision, particularly CNNs, which process images hierarchically using alternating convolutional and pooling layers. These layers extract local and global features, improving classification performance. CNNs excel at representing translation-invariant features, unlike traditional methods sensitive to localization. CNNs, originally designed for grayscale images, were adapted for color images. Image classification pipelines consisted of a feature extraction network and a classifying network, with successful implementations and publicly available pre-trained models. Concerns about network architecture growing in complexity were mitigated, as deeper networks showed better performance even with more parameters. Furthermore, CNNs improved robustness against rotation, distortion, and occlusion compared to traditional methods. Most research endeavored to find optimal networks for a specific dataset. Fine-tuning pre-trained models on new datasets reduced training costs. Artificial networks mimicked the human visual system's three-layer hierarchical feature extraction. CNNs, pre-trained on the ImageNet database, achieved state-of-the-art results in image classification and feature extraction on diverse datasets. This latent space representation approach facilitated effective representation transfer across domains and tasks. While transfer learning concepts existed since the 1990s, recent advances in deep learning and CNNs sparked renewed interest. Past experiments focused on SVM classifiers. Current investigations seek to deepen understanding of properties responsible for effective transfer.

3.1. Traditional Methods vs. Deep Learning

Image classification serves as a connective bridge between the visual and numerical domains. Traditionally, handcrafted image features such as edges, textures, color histograms, and SIFT were considered the norm. However, since 2012, database-associated features and deep learning have surged in popularity. On ImageNet, consumers noticed the surprising performance of deep neural network classifiers that mitigated the vanishing gradient issue through stochastic gradient descent (SGD), filters starting from convolutions with suitable initial values, and pooling operations. Their adaptive learning rates via RMSprop or AdaGrad variants yielded ever-acting non-stationary optimization processes directly on large and obtuse functions. To benefit from the large labeled datasets in the back end, pre-training techniques were adopted, which involved stochastic unsupervised training through the forward paths of the convolution layers or the whole network before fine-tuning the top classifier with back-propagation. These techniques still yield valuable features for SVM or nearest-neighbor classifying in the absence of labeled training samples. Despite the apparent simplicity of these operations, they drastically impacted the performance of classifiers applied to trained databases.

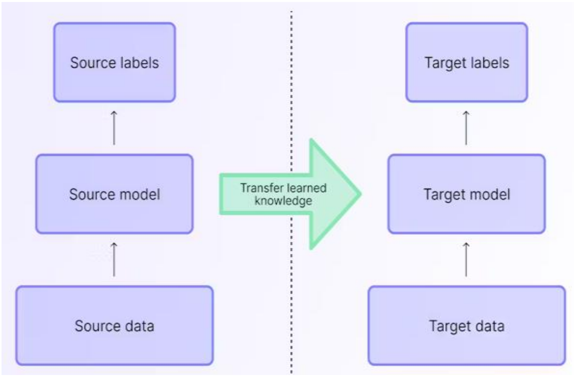
To capitalize on the pre-trained models and boost system performance, two common industrial adoption techniques were implemented: unfreezing layers to fine-tune deeper convolutions on smaller databases, or freezing deeper convolutions and feeding features generated by current filters to SVM with median complexity. Recognizing the need for workable features, the domain transfer techniques were employed, alongside the traditional bag-of-words visual vocabulary methods or the recent Fisher vectors within Gaussian Mixture Models. In light of the recent resurgences of professional AI-for-all systems at the foreground of social networks and innovative smart devices, this treatise first presents conventional machine learning solutions and their popularity challenges by deep learning methodologies applied on large-view databases.

3.2. Transfer Learning

The image classification landscape is diverse, with innumerable categories and vast volumes of data generated every second. As the dataset grows, training a deep neural network from scratch becomes more daunting, usually demanding specialized hardware and extensive time. Maintaining and optimizing the training process adds further challenges. In such situations, a model trained on a similar task can be a significant advantage. Fine-tuning a pre-trained model adapts it to a new task or dataset with remarkable efficiency. This adaptable skill is called transfer learning. This section delves into transfer learning techniques, detailing their utility and scope. Transfer learning is transferring knowledge acquired through one task to another. It has gained traction due to the need for a machine-learning model to predict any graph with real-world applicability, with popular prediction tasks being text classification and image classification. Tasks are often diverging from those in data and prediction capabilities, while datasets may be limited or noisy. For such scenarios, transfer learning techniques can be used to predict or extract data from images with limited or no prior training datasets. Transfer learning is better than starting from scratch or training highly task-specific models, and it can be collaborative and spillover across disciplines. While there is a vast space of candidates in transfer learning, the approaches in nature - "How transferable and similar are the source and target tasks?" - and its realizations in predictive analytics - "What methods to transfer?" - are easy to categorize.

Visual data analysis necessitates robust deep learning methods to achieve acceptable performance reliably. Such methods should be insensitive to noise, occlusion, viewpoint change, and deformations while invariant to modifications such as cropping, translation, or low contrast. For the complicated dynamics of visual data analysis tasks, generalization from diverse tasks with a varying number of classes is crucial. Image classification is the most widely explored visual data analysis task in deep learning, and it is also the basis for higher-level data analysis tasks such as object detection and image retrieval. In object detection, images are annotated by their bounding boxes, and tasks may have a much larger number of classes than those in datasets, while images may have a complicated inner visual category hierarchy. This renders the assumption of i.i.d. (independent and identically distributed) of training and testing data invalid. The best-known deep learning architecture, the convolutional neural network (CNN), was trained from scratch for image classification. This might not be feasible for many categories and datasets, recasting image classification into a multi-class problem. Nonetheless, CNNs have been trained on a large database like ImageNet. Thanks to the varied classes and images, CNNs trained on ImageNet have learned generic visual concepts and features that are shared across datasets and different computer vision tasks. Fine-tuning a pre-trained CNN model on ImageNet for a specific dataset or task with a small number of labeled samples is a promising transfer learning technique. Such models usually outperform those trained from scratch and require less training time and labeled data. Transfer learning can be attempted to extract and analyze hidden visual concepts modeled by various activities.

Fig 2 : Transfer Learning Knowledge



4. Recent Advancements in Deep Learning

Deep learning, a subset of machine learning techniques based on artificial neural networks with representation learning, has gained popularity in recent years, especially with the availability of a tremendous amount of visual data on the internet and the rapid progress in deep learning hardware. The paper briefly summarizes some recent and key developments in deep learning with a focus on visual data and image classification to analyze the future of visual data analysis. Attention mechanisms have advanced rapidly in the domains of image and video classification. Attention is a key concept studied in neuroscience and psychology to unravel the perception of objects and scenes in visual data. In computer science, attention was originally considered to be an information bottleneck to reduce the burden of understanding complicated objects and scenes. Recently, attention mechanisms have emerged in visualization tasks, such as text translation, image understanding and generation, and video comprehension. Attention mechanisms process separate information streams with attention filters to highlight the critical visual characteristics; simultaneously, the remaining data and attributes are discounted and eventually neglected as the image relevant to text queries.

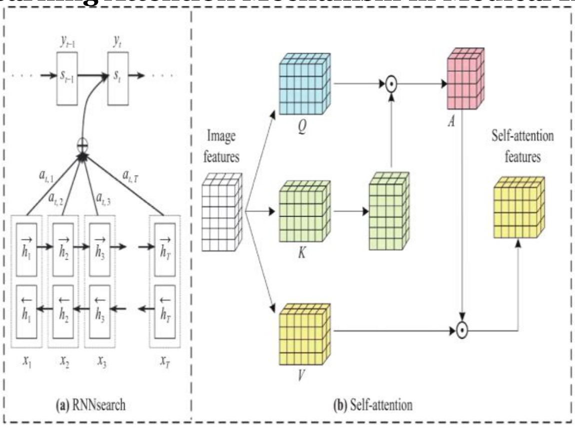
Attention models were initially designed for text-based tasks and were directly transferred to visual domains with several restrictions. Subsequently, image-specific attention networks were designed for image captioning and image question-answering tasks by coupling filters, mechanisms, and visual characteristics to textual attributes and semantic properties. The video intelligence branch began to develop attention mechanization to select video segments salient to given questions or textual queries while neglecting other irrelevant sequences. Multimodal attentional networks were then researched, which focused on developing complex interactions between vision and language for image-text or video-text identification and retrieval. GANs are learning mechanisms where two neural networks compete with each other. A generator network creates fake data, while a discriminator network distinguishes between real and fake data. They are trained simultaneously, improving each other's performance. GANs were originally designed for image generation from random latent variables and subsequently extended to various data types, such as text, image, audio, and video, and complex data structures involving multimodal inputs and outputs. GANs were initially designed to generate images without supervision and were used in many image transformation tasks with paired images to hone the transformation procedure.

4.1. Attention Mechanisms

Attention mechanisms have been a groundbreaking advancement in image classification tasks and computer vision problems. Traditionally, convolutional neural networks (CNNs) fully fed all information from their input features. This method paid equal attention to the input regardless of importance or relevance. Human visual systems, however, focus on analyzing certain important visual data while ignoring other information for more resource-efficient processing. Inspired by this biological approach, attention mechanisms selectively enhance important features regarding their relevance for the learning task ahead, while diminishing less relevant information. Such selective feature processing thereby enhances the network's learning ability for visual data. This technology also enhances the interpretability of CNN models by producing attention visualization maps that indicate where the models focus on analyzing images. As a result, attention mechanisms have become popular in deep learning research. While most of the attention-related works focus on text inputs in natural language processing tasks, new approaches have been proposed in recent years for the incorporation of attention mechanisms in image classification and other computer vision tasks.

Attention mechanisms can be generally categorized into spatial attention, channel attention, and their combination. Spatial attention enhances important spatial regions regardless of their input channels. In this case, where to focus on is spatially determined. Channel attention focuses on analyzing certain channels of input features regardless of their spatial position. In this case, a specific feature channel to focus on is determined. Both variants can simply be efficiently appended to CNN architectures. By viewing attention as a mechanism to enhance feature representation learning on a specified task, attention mechanisms can be applied to any CNN architecture trained on any task with ease.

Fig 3 : Deep Learning Attention Mechanism in Medical Image Analysis



4.2. Generative Adversarial Networks (GANs)

Generative Adversarial Networks (GANs), developed by Ian Goodfellow and colleagues in 2014, are a type of deep learning architecture consisting of two networks: a generator and a discriminator, which are trained together in an adversarial process. The generator creates new data samples, while the discriminator evaluates them. This approach allows GANs to generate realistic images and has been successfully applied in various domains. The architecture of GANs includes two neural networks, each with its performance objective. The generator aims to produce data that matches the training dataset, while the discriminator's goal is to differentiate between real and generated data. To train GANs, a mini-max game is formulated where the generator's strategy is to minimize the probability of the discriminator correctly classifying its outputs, and the discriminator's strategy is to maximize this probability.

GANs train the generator and discriminator based on the outputs and errors of their respective networks. The training process ends when both networks reach optimal parameters or converge, resulting in the generator producing data indistinguishable from the training dataset. This ability to generate images similar to the training set positions GANs as a potential development tool for the art and design industries. Training GANs, however, can be challenging and may lead to issues like instability, difficulty in convergence, and the presence of artifacts in generated images. To address these challenges, several modified GAN architectures have been proposed, including WGAN-GP, Pix2Pix, CycleGAN, and StyleGAN. These architectures target specific problems and enhance the capabilities of GANs in the fields of image generation, style transfer, and inpainting. Overall, GANs represent a promising field of research in material science for discovering new materials with desired properties.

Equation 2 : Consider this neural network

It has an input $X = (X_1, X_2)$,
a hidden layer $h = (h_1, h_2, h_3)$,
and an output $a = (a)$
The layers h and a has sigmoid activation function.
Input X is

$$X = \begin{pmatrix} 1 \\ -1 \end{pmatrix}$$

The weight matrix for X-h is

$$W^X = \begin{pmatrix} 1/2 & 1/2 \\ 0 & 1 \\ 1 & 0 \end{pmatrix}$$

The weight matrix for h-a is

$$W^h = \begin{pmatrix} -1 \\ 1/2 \\ 1/2 \end{pmatrix}$$

5. Applications of Deep Learning in Image Classification

The integration of deep learning in image classification has manifested significant applications across various fields, including medical imaging and autonomous vehicles. Each application presents unique challenges and proprietary solutions recognized as its contribution to the overall field. With the advancements in artificial intelligence, there has been the capability of machines to perform large domain-specific tasks to a reasonable degree of accuracy. This includes understanding visual data and automating its associated decision-making tasks by simulating human-like perception. Deep learning is now the predominant approach that drives many computer vision applications, thanks to the extensive dataset availability, advanced computing devices equipped with parallel architectures such as GPUs, and the introduction of models and techniques that allow for the intensive representation learning of data in a hierarchical way. It has been recognized as the most reliable and accurate approach for the large-scale domain of analysis of visual data, including faces, people, animals, insects, flowers, text, and more.

The application of deep learning in image classification encounters a challenging domain that is wide and diverse, such as its constituent categories and the associated non-distinctive visual characteristics. This involves the efficient and effective learning of domain-invariant and discriminative representations of data for the automation of domain-specific visual data analysis tasks, such as categorization, detection, and segmentation in the deep representation learning frameworks. There are many categories with thousands of classes with such image datasets, resulting in a computationally intensive learning task. Moreover, there are many recent datasets with images captured in real-world conditions with complex backgrounds, poses, occlusions, views, scales, and more that exacerbate the given task. This challenge is known as the dataset and domain-shift problem. The recent success of deep learning in the visual domain includes a multitude of domains where each has unique characteristics, challenges, contributions, and considered strategies or techniques. In each case, the applicability of the techniques with consideration of the pipeline of deep learning and potential future directions is discussed. Attention is paid to the visualization of the content using figures and analysis of the associated challenges, strengths, and concerns to provide a comprehensive understanding of the current state of the art and potential future paths concerning deep learning and image classification. The main aim is to explore wide and diverse domain-specific visual data analysis tasks that have been the subject of deep learning and image classification. The specific tasks of each domain are not exhaustive.

5.1. Medical Imaging

With the exponential growth of healthcare data in the form of medical images, the ongoing digitization of healthcare systems brings forth new challenges and opportunities for leveraging deep learning. Here, it explores the state-of-the-art deep learning models, more specifically, convolutional neural networks (CNNs), and their extensions for the classification of prominent medical imaging modalities including 2D radiography, mammography, 3D CT as well as magnetic resonance (MR) images. Besides the development of novel deep learning architectures for medical imaging, several techniques that can be beneficial for the design of neural networks are presented as well. Deep learning-based medical image classification and screening systems are investigated, which have been shown to tackle critical shortcomings of the traditional approaches, such as the demand for large numbers of expert features and long processing times. Given the plethora of potential solutions in the literature, an established benchmarking methodology is proposed for the selection of optimum networks and configurations concerning the evidence available. These approaches can serve as useful tools for researchers and practitioners who may begin to explore deep visual content analysis applications for medical images.

Over the past years, deep learning techniques, specifically convolutional neural networks (CNNs), have been at the forefront of image classification, segmentation, and reconstruction advancements. Given the success of the aforementioned techniques, the thought of applying them to medical images, the most analyzed images in the world, arises. With the increasing digitization of healthcare systems, terabytes of medical images are being created every day, and given their inherent characteristics such as dimensionality and noise, traditional image classification techniques fall short of maximizing their potential for analysis. On the contrary, CNNs, and their extensions, have proven to be very powerful classifiers of natural images widely used in numerous real-world applications. With the unprecedented amount of available healthcare data, there is an increasing demand for its understanding to tackle the very challenging problems that come forth in today's world. A confluence of factors has made possible the training of deep learning pipelines. Specifically, the exponential growth of training data Internet databases, superior computing power of GPU architectures, and improved architectural design of neural networks have emerged as a few enablers of the adoption of deep learning approaches. From the rise of these very simplistic, yet powerful tools, their architecture has been heavily investigated to achieve state-of-the-art results in image classification. However, the design of the network topology is far from trivial, and networks' parameters can take days to be configured. With the advent of open-source codes and free learning resources, the field has rapidly grown, gaining much interest in other application domains.

Equation 3 : Iterative and mixed-spaces image gradient inversion attack in federated learning

Input: target model f_θ, gradients $\nabla\theta$ from local batch $\mathbb{D}^B$ $\{(\boldsymbol{x}_i, y_i)|i \in B\}$, reconstructed label $\boldsymbol{y}^*$, generator G, internal iterations (M, N), external iterations T.
Output: reconstructed images $\{\boldsymbol{x}_i^*|i \in B\}$.
CMA Configuration:
  Initial Parameters $(\mu_{\boldsymbol{z}}, \Sigma_{\boldsymbol{z}})_i \leftarrow (0, I) \quad i \in B$;
  Budget K.

for T *iterations* **do** `// External Loops`
  for M *iterations* **do** `// Latent Space Search`
    foreach $i \in B$ **do**
      $\{\boldsymbol{z}_i\}_{1:K} \leftarrow$ `SampleCMA` $((\mu_{\boldsymbol{z}}, \Sigma_{\boldsymbol{z}})_i)$;
    $D_{\boldsymbol{z}} \Leftarrow \mathcal{L}(\frac{1}{B}\sum\nabla\ell(f_\theta(G(\boldsymbol{z}_i^*))); \nabla\theta) + \mathcal{R}_{\boldsymbol{Z}^*}$;
    foreach $i \in B$ **do**
      `UpdateCMA` $(\{\boldsymbol{z}_i\}_{1:K}, \{D_{\boldsymbol{z}}\}_{1:K})$;
      $\boldsymbol{z}_i^* \leftarrow$ `SampleCMA` $((\mu_{\boldsymbol{z}}, \Sigma_{\boldsymbol{z}})_i)$;
  for N *iterations* **do** `// Parameter Space Search`
    $D_{\boldsymbol{w}} \Leftarrow \mathcal{L}(\frac{1}{B}\sum\nabla\ell(f_\theta(G(\boldsymbol{w}_i^*))); \nabla\theta) + \mathcal{R}_{\boldsymbol{W}^*}$;
    foreach $i \in B$ **do**
      $\boldsymbol{w}_i^* \leftarrow$ `UpdateWithAdam` $(D_{\boldsymbol{w}})$;

foreach $i \in B$ **do** $\boldsymbol{x}_i^* \leftarrow G(\boldsymbol{z}_i^*, \boldsymbol{w}_i^*)$;
return $\{\boldsymbol{x}_i^*|i \in B\}$.

5.2. Autonomous Vehicles

As technology continues to evolve, the automotive industry is taking steps towards increased automation, and a popular topic today is the utilization of deep learning approaches for the analysis of image data in cars. One idea behind this is to have a fully autonomous vehicle that can operate without a human driver. A complicated deep learning approach called convolutional neural networks (CNN) is proposed here for the classification of images captured from a vehicle's dashboard camera into four different classes: roads, traffic lights, vehicles, and buildings. With new technology such as LIDAR, radar, and video cameras, vehicles can sense, analyze, and understand their driving environments to make safe and efficient driving decisions. Video cameras, mounted on vehicles, capture images of the environment as the vehicle moves along the road network. A driver or an "agent" has to interpret the captured images to understand the driving situation. For example, whether there are pedestrians on the road, or whether it is safe to make a right turn or overtake another vehicle.

It has become crucial to develop intelligent control systems or agents that can take automated safety actions based on the understanding of the driving environment. Such intelligent control systems need to classify objects in time-critical driving situations, such as "Is the traffic light green or red?" The technology that has emerged in recent years for the design of these intelligent control systems is deep learning. Deep learning techniques can be utilized for the automatic classification of large datasets containing high-dimensional input data that require complex features to be modeled, such as images of driving environments. The approach taken in this study involves mapping the understanding of the driving environment to classification tasks and utilizing CNN for the classification of the environment's images. CNNs are a type of feed-forward neural network composed of multiple layers that is especially well-suited for the modeling of high-dimensional image data. Although the investigations are not conducted directly using video images, the modeling of image data is, nevertheless, still of high interest in autonomous cars, as they are being equipped with increasingly cheaper video cameras. CNNs have previously been successfully utilized for object classification in other applications such as face detection and recognition. In this study, the focus is on the classification of image data for a fully autonomous vehicle and not on the modeling of other driving actions. Image classification means that a vehicle's dashboard camera, which captures images of its driving environment is assumed to exist, and object classifications regarding the content of the captured images need to be created.

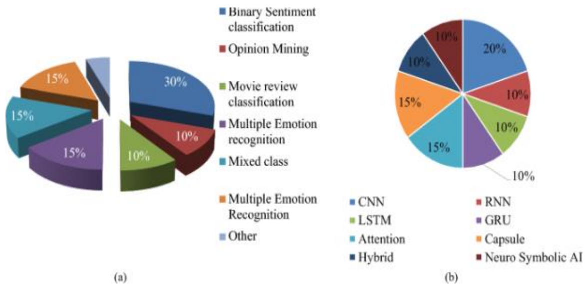
6. Challenges and Future Directions

As content and capability requirements continue to rise, researchers and practitioners will encounter several interesting opportunities to help overcome challenges in the state of the art. However, even as capabilities continue to grow, new barriers will arise in the assessment of visual data analysis. Deep learning algorithms for image classification have been increasingly successful in recent years, rivaling or exceeding the performance of traditional image classification technology in several areas. Commonly used deep architectures include variants of convolutional neural networks (CNNs), re-convolution networks (RCNs), and residual neural networks (ResNets). However, challenges remain. Several deep architectures use up so many resources that practical deployment on small systems is next to impossible. A notable example is ImageNet, which requires a GPU cluster with 1000 powerful GPUs and extensive energy, in addition to normal data pre-processing needs for parallel analysis with an array of systems. Another approach is to use blind localization or multi-scale pooling layers to extract features for classification or in classifiers trained on pooled statistics from localized regions. Though it overcomes issues regarding object localization and occlusion, it nevertheless allows features to be generated that do not make full use of knowledge about class membership. The increase in off-the-shelf feature extractors and spatial models has made visual data analysis dependent on specific types of visual content, thus limiting the impact on deeper architectures.

Deep algorithms for image and video have grown in number and complexity, alongside enhanced potential, thus enabling the integration of these capabilities into diving platforms. This transplantation enables more efficient use of capabilities while also expanding the range of possible operations. Current technologies allow near-continuous data streaming during inspection operations, thus producing a large and rapid influx of possible acquisitions. Systems developed for the image analysis of generic visual content are currently too complex and demanding in terms of the requirements of visual data preprocessing for the diversity of domains anticipated for maritime and underwater visual acquisition and analysis. In this regard, whilst challenges in marine data acquisition are being overcome, new challenges in visual data analysis using deep architectures will be faced.

Two important challenges will be the dominant driving force for research in visual data analysis moving forward. The most important line of inquiry will be visual data privacy and ethics, especially marine surveillance. The complexity of deep architectures will compound concerns about compliance with the requirements of public ethical practice and prudence, thus prompting calls for transparency and interpretability in conjunction with complex geospatial data.

Fig 4 : Challenges and future in deep learning for sentiment analysis



6.1. Data Privacy and Ethics

The rapid adoption of deep learning methods has renewed debates and concerns regarding data collection, storage, and usage, especially personal and sensitive data. This concern is general across various domains and is not specific to computer vision or deep learning. Various governments have tightened regulations regarding data usage for commercial purposes. Examples like the European General Data Protection Regulation (GDPR) and the California Consumer Privacy Act (CCPA) state how, when, to whom, and where data can be used. Most deep-learning classification models learn directly from raw data, depending significantly on the data of other parties. These models are sensitive to data leakage and can unintentionally infer the type of data used during training. For instance, a facial recognition model trained on a dataset composed of Christians and Atheists could potentially identify an individual's religious beliefs. Such risks raise pressing questions about the ethics of data usage and commodification.

Data privacy indicates the piece of information related to a single individual that a third party doesn't possess. It includes scribe, biometrics, employment details, address, personal interests and hobbies, past and current medications, and more. All this data helps to build an individual profile about an individual. When this data is shared by people, in online space and otherwise, concerns arise regarding its misuse. Some of the many risks of data misuse include danger in the job market, blackmailing, stalker attacks, emulation of fraud crimes, being targeted by crime organizations, and identity theft. All these issues force people to think about their data more than before and, in many cases, take preventive actions.

Facebook is currently on trial for creating a political advertisement based on the misuse of personal data. Other data misuse stories include Cambridge Analytica, Target misusing the personal data of their clients to derive their spending habits, and Marriott's compromise of hundreds of millions of pieces of personal data from their customers. Sensitive data arises when a data party might infer additional sensitive details about a data subject beyond the content of a data record. For example, an individual's credit card purchase history is not outlined by gender, but a third party could infer this detail. In recent years, there has been a rise in black-box machine learning classification models; even though they yield high-class discrimination accuracy, it is impossible to know how these models function. Systems might be biased against one group either because the training data is polluted or due to how models learned the data. The black-box nature of a classification model also impacts its robustness: an undetectable perturbation can change a model's decision for adversarial examples.

6.2. Interpretability and Explainability

Deep learning methods have achieved remarkable performance, chiefly due to their superior capabilities in modeling complex relationships present in high-dimensional visual data. However, gaining a deeper understanding of what is achieved in these models' hidden layers remains one of the grand challenges within the deep learning domain. The vision to create artificial intelligence systems that can perform visual tasks similarly to a human requires a comprehensive comprehension of the deep learning architecture on top of which these systems are built. Basic neural network models such as convolutional neural networks (CNNs) are often conceived as a "black box" with various levels of complexity that obfuscate an intuitive understanding of how internal representations are created or which features for classification decisions are prioritized. Rising questions about the interpretability and explainability of deep learning methods' decisions to untrained audiences are regarded as vital to developing visual analysis systems that are trustworthy and can be seamlessly integrated into the decision-making processes.

Interpretability adds to classical machine learning models the human understanding of the model internals and the significance of its decisions. Various interpretability levels can be defined for still largely unexplored hidden layers, individual filters, or neuron activations, leading to comprehending which features are extracted, suppressed, or given priority. Conceptually simpler to provide, the interpretability of last-hidden layers is limited, as the overlapping features of various visual concepts become dominant. A higher degree of accountability is reached with the decision-making layer, where each decision is outlined with contributions of individual features given to the model input. Such an output is often presented with a focused visual inpainting that illuminates features for the target class while diminishing those for alternative outputs. The explanation model not only specifies what is the focus of the decision but, through the model architecture, reveals how perceptions are propagated to produce the output.

Human-level understanding means two-way communication between models and users. Standardized measures need to be developed to focus on further conceptual issues to be addressed to realize the interpretability potential. With a growing range of models capable of highlighting additional layers, the number of potential interpretations is also increasing, leading to difficulties in intuitively comprehending the results and drawing reasonable conclusions. Competing methods should be rigorously evaluated regarding accuracy, sensibility, and stability vis-a-vis variations in model parameters and datasets. Model interpretation should accompany a broader interpretation of model uncertainty, as the counting of weights and correctness of decision-making are insufficient in determining the appropriate output.

7. Conclusion

Although early approaches to image classification systems utilized various techniques, including pattern recognition and machine learning, most systems relied on the use of a particular set of low-level features. These features, combined with classifiers such as SVMs or Random Forests, defined the system. As the quality of the selected features is often closely linked to the success and robustness of a system, the attempts to search for other kinds of low-level features in the literature and to use them in combination with other classifiers all follow the same trend. Fortunately, deep neural networks remove the necessity for designing the feature set. "Trainable" feature extractors are built into the architecture of a deep neural network and fully optimize the feature set, thus making it robust to the task of interest. A strategy that needs to be followed to obtain optimum networks is to search for techniques and configurations that allow the construction of deeper and more complex networks. However, such is the scenario of image classification tasks, being the identification of the main approaches in neural networks such as Convolutional Neural Networks (CNNs) or Hierarchical Residual Networks (ResNets).

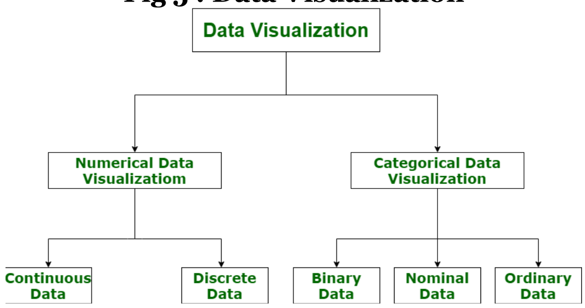
These networks extract hierarchical representations of the input image, almost automatically extracting the features of interest. Chains of convolutional layers filtering different feature maps are followed by pooling layers, which down-sample the output of the convolutional layers and start the cascade of deeper layers. As the networks are deep, they allow the extraction of abstract features, moving from edges and pixels in the input image to textures and shapes, or objects, in the deepest layers. Then, networks end in Fully Connected Layers mapped to the class labels, which obtain the activity of the previously hidden layers and, with the use of classifier functions, output the network decision. Although very different in build, Hansen & Dorsey's wavelet multilayer perceptrons and CNNs share the same idea of a feature extraction stage based on the utilization of a convolution operator. Such an operator minimizes the number of weights of the position-invariant architecture of the neural network, resulting in networks with considerably reduced complexity and, thus, much faster to train. CNNs give the possibility to choose the architecture complexity of the network, determining the number of filters and pooling layers, allowing the customization of the image's representation to be extracted. This makes CNNs suitable for visual data analysis and various other types of signals such as audio, wireless communications, or biomedical signals.

7.1. Implications for Visual Data Analysis

Deep learning techniques, particularly convolutional neural networks (CNNs), have significantly advanced image classification, leading to a better understanding of visual data and influencing various research fields and application areas. The continuous emergence of digital images from multiple sources, such as smartphones, drones, and security cameras, has driven the need for effective tools to analyze, understand, and classify image data. These requirements have paved the way for several key implications and discussions in the area of visual data analysis. As a result of this progress, several implications in the area of visual data analysis have significantly contributed to a better understanding of visual data and their uses in different research fields and application areas. The continuous emergence of millions of images daily from multiple sources, such as mobile phones, satellite imagery, surveillance cameras, and drones, has intensified the requirements for effective tools to analyze and understand the information behind these visual data. Digital images from multiple sources have emerged at a rapid pace, producing a huge quantity of visual data containing rich information. It is imperative to analyze this visual data either automatically or effectively if it cannot be comprehended and understood due to its large quantity. This provides numerous opportunities for researchers who come up with different methods and techniques to classify and facilitate a better understanding of visual data.

Though images and videos were initially analyzed by the use of classical features, handcrafted features are being coupled with advanced machine learning techniques instead of directly feeding raw pixels to classifiers. Machine learning methods have to be trained on large and task-specific datasets, and the requirement of large datasets may limit their potential areas of application and effectiveness. As opposed to machine learning methods, deep learning techniques have been hugely successful by automating the feature extraction process on imaging tasks. Deep learning approaches, mainly CNNs, are the current state-of-the-art for image classification. With the availability of datasets containing millions of images and substantial development of hardware and processing capability, CNNs are now being used as a better alternative to classifying images. As the use of digital images has intensified in different applications, better comprehension of visual data and their analysis has attracted the attention of different research fields, requiring the development of sophisticated tools to analyze these visual data from different sources.

Fig 5 : Data Visualization



7.2. Future Trends

A plethora of upcoming trends and advancements in computer vision are expected to shape the landscape of visual data analysis in the ensuing years. This burgeoning domain, flourishing significantly in recent years with the advent of deep learning, has dealt with systems capable of interpreting and analyzing images in a manner akin to human cognition. Consequently, computers can recognize and process the internal structures of recognized objects or situations. The major future trends likely to grip the field in the next few years include improvements to existing architectures and the rise of novel ones. Regarding improvements, ResNet remains a good network to expand in both depth and width. Additionally, the notion of pyramids could be explored further, exemplified by efforts at Google. Moreover, augmentation is seen as one of the main bottlenecks to low prior requirements for wide dissemination of GPGPU systems. Consequently, it is necessary to investigate generational models that could automatically enhance images and obtain richer data with minimum human effort. In terms of new architectures, four major thrusts of very recent importance could be potentially further developed. First, the less common use of modulation applied to inter-layer communication could yield ensemble classifiers that encompass a variety of perspectives instead of relying entirely on a unique one. Secondly, networks that are automatically constructed via combinatorial methods, akin to original human effort (such as projects at Google), may emerge to vastly accelerate the process.

Thirdly, the shift from isolated parts to whole objects across the whole pipeline could serve as a potentially interesting radical change in perspective, possibly enhancing accuracy. Finally, the more innovative idea of recursive deep learning based on Lisp notions (as per an NYU project) may lead to substantial networks, aiding in understanding the process of cognition itself. All these points could lead to significant advancements in the field of computer vision. Further steps in research accomplished in the last few years will also be pursued to enhance the theory and application domains. Continuous improvements of already provided results are anticipated. Notably, a recently posted code on request for the image search engine developed is in the process of validation, after which it will be made public and its usability reported. Thereafter, it will be considered developing its still-absent complement for video processing, anticipated to be an important niche given the rapid growth of such data on general-use computers. On the other hand, considering different applications of reflection, context recognition is expected, as there are many realistic situations affecting accuracy in precisely this way, presently unexplored. Similarly, an onboard vehicle situation image pre-classification method is awaited for a slightly different perspective. In the more industry-oriented domain, new concepts for autonomous market kiosk design with reasonably advanced interaction abilities are awaited.

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