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# Mathematical Approach in Image Classification using Regression

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**Abstract:** *This study presents a comprehensive evaluation of logistic regression in contrast to a hybrid model combining VGG16 with logistic regression for image classification tasks. The research findings illuminate a striking performance disparity between these two approaches, shedding light on the profound impact of integrating deep learning techniques into image classification. The transition from logistic regression to the VGG16-based hybrid model marks a notable turning point in our investigation. The VGG16 architecture, renowned for its prowess as a feature extractor, showcases an impressive 53.33% surge in accuracy compared to the conventional logistic regression model. This substantial leap underscores the model's capacity to decipher complex image characteristics that elude traditional statistical methods. Furthermore, precision, a crucial metric in classification tasks, experiences a substantial 53% augmentation when adopting the VGG16 hybrid approach. This enhancement signifies the hybrid model's ability to minimize false positives, making it particularly valuable in scenarios where precision holds paramount importance. Equally noteworthy is the substantial 54% improvement observed in both recall and F1-score, emphasizing the VGG16 hybrid model's remarkable capacity to identify and retrieve a higher proportion of true positives while maintaining a balance between precision and recall. This not only amplifies the model's ability to correctly classify images but also mitigates the risk of overlooking relevant instances. These compelling findings underscore the critical role of deep learning, specifically convolutional neural networks (CNNs), in the realm of image classification. The utilization of CNNs, exemplified by the VGG16 architecture, emerges as a game-changer, enabling the capture of intricate image features and patterns that traditional logistic regression struggles to discern. Generally, this study advocates for the integration of advanced deep learning techniques, like VGG16, in image classification endeavors. The substantial performance gains witnessed in accuracy, precision, recall, and F1-score reinforce the pivotal role of convolutional neural networks in enhancing the effectiveness of image classification tasks. By harnessing the power of deep learning, we unlock new horizons in image analysis, paving the way for more accurate and efficient classification systems.*

**Keywords:** CNN, Logistic Regression, Supervised Learning, VGG16

## I. INTRODUCTION

Image classification remains a compelling and ongoing challenge in the field of computer vision, as it empowers machines to acquire knowledge autonomously, without the need for direct human intervention [1][2]. This task revolves around the automatic categorization of images into predefined classes based on their visual content. One prominent approach employed in this endeavor is pattern recognition, which involves the extraction of distinctive features from the objects or elements under examination [3]. Essentially, this method seeks to characterize information by identifying and discerning significant features within the objects themselves [4].

While Convolutional Neural Networks (CNNs) have achieved remarkable breakthroughs in the realm of image classification, the application of classical statistical techniques, such as logistic regression, continues to captivate the interest and curiosity of researchers [5]. This paper embarks on an experimental journey, aiming to explore a hybrid approach by combining the formidable capabilities of a CNN pre-trained architecture, like VGG16, with logistic regression.

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Logistic Regression, traditionally a mathematical concept, has primarily been utilized for predicting continuous values [6]. From a statistical perspective, it serves as a powerful tool for gauging the significance of correlations among variables contained within a dataset, elucidating the intricate interconnections among these variables [7]. In the context of digital image processing, images are often characterized by pixel values, which are represented by arrays of numerical data serving as descriptors for class representation [8]. These values are generated through feature extraction techniques. Subsequently, these extracted features undergo supervised machine learning, with logistic regression playing a pivotal role in modeling the relationship between input features and the probability of belonging to specific classes [9]. Remarkably, logistic regression, once designed for binary classification, has evolved to accommodate problems involving more than two possible outcomes [10].

On the flip side, Convolutional Neural Network Architectures (CNNs) have emerged as a formidable force in feature extraction. This feature extraction process has found particular relevance in image classification, especially in applications like biometrics. The innate ability of neural networks to autonomously learn features from raw pixel data has revolutionized the landscape of computer vision [11]. CNNs have consistently demonstrated their mettle in cutting-edge image classification tasks, primarily owing to their aptitude for capturing intricate and complex visual patterns through the integration of deep convolutional layers [4][11]. However, it's worth noting that CNNs often demand substantial computational resources and extensive labeled datasets for effective training, a limitation that can hinder their application in resource-constrained environments.

By synergizing the interpretability and data efficiency of logistic regression with the feature extraction capabilities inherent in the VGG16 CNN architecture, this research embarks on an ambitious experiment aimed at integrating these mathematical techniques to construct a face recognition model. The primary objective here is to leverage logistic regression as a complementary model to VGG16, harnessing the unique strengths of each to craft an innovative hybrid system for the classification of facial images. The initial phase of the experiment involves the application of pure logistic regression, followed by another experiment in which VGG16 is utilized for feature extraction in conjunction with logistic regression. Both experiments are rigorously evaluated using metrics such as accuracy, precision, recall, and F1-scores to discern their respective performance characteristics.

## II. METHODOLOGY

### 2.1 Hardware

TABLE I: Hardware requirements

| Hardware Components | Specification |
|---|---|
| **CPU** | **Intel® Core™ i7-8700 CPU @ 3.20Ghz 3.18Ghz** |
| **Memory** | **16 GB RAM** |
| **Storage** | **1 TB HDD** |
| **GPU** | **6GB NVIDIA GTX-1660** |

### 2.2 Software

TABLE III: List of software

| Name | License |
|---|---|
| **64-bit Windows 10** | **Proprietary** |
| **Anaconda Navigator 2.3.2** | **Open-Source** |
| **Spyder 5.3.3** | **Open-Source** |
| **Python 3.9.15** | **Open-Source** |
| **OpenCV 4.6.0** | **Open-Source** |
| **Tensorflow 2.10.0** | **Open-Source** |
| **Matlab R2020a** | **Open-Source** |
| **Matlab R2020a Deep Learning Toolbox** | **Open-Source** |
| **Adobe Photoshop** | **Proprietary** |

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### 2.3 Dataset

Face image collection was performed to support five distinct categories, with each category consisting of precisely 30 images. The sources of these images were diverse and drawn from various reliable outlets, including Facebook and personal photo album collections. This strategy was adopted to ensure a broad spectrum of visual content, encompassing different angles, lighting conditions, and backgrounds relevant to the specific context of each class.

The annotation procedure played a crucial role following the capture of these images. To create a ground truth dataset, each image was meticulously labeled with the appropriate class.

In Figure 1, you can find a sample of images used in this study, offering a visual representation of the dataset.

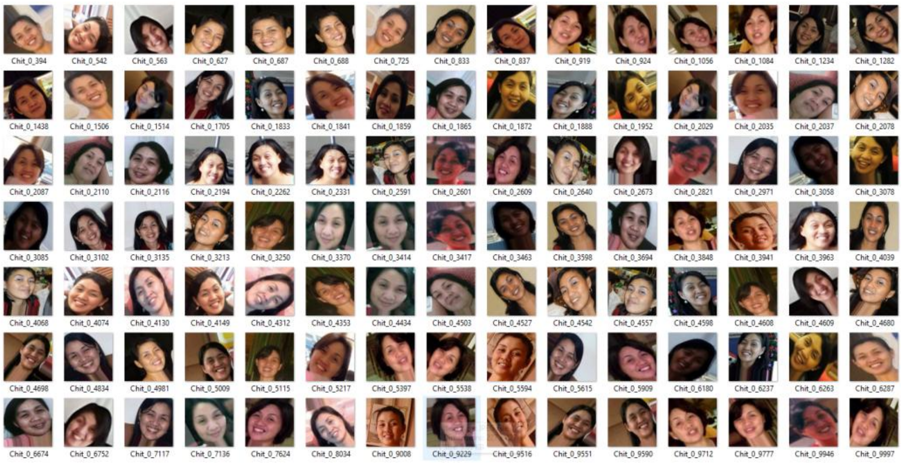

Fig. 1. Sample of the image used in the study

### 2.4 Training

In the inaugural experiment, a straightforward methodology was employed to address a classification challenge, relying solely on the principles of logistic regression. This entailed the mapping of the dataset's features to a logistic function, a method effectively used to estimate the probability of a given data point's affiliation with one of the defined classes. This approach, while simple, provided an essential baseline for evaluating the model's performance and served as a starting point for more intricate investigations.

In contrast, the subsequent experiment embarked on a more sophisticated path by incorporating the VGG16 convolutional neural network (CNN) architecture in conjunction with logistic regression. VGG16, renowned for its exceptional performance in image classification tasks, owes its reputation to the presence of deep convolutional layers that allow it to extract intricate and hierarchical features from complex visual data. The fusion of VGG16's deep learning capabilities with logistic regression introduced a new dimension of complexity and adaptability to the model, enhancing its potential to excel in image classification tasks.

Both experiments underwent rigorous evaluation using a comprehensive suite of performance metrics, including accuracy, precision, recall, and F1-score. These metrics provided a holistic assessment of the models' capabilities and enabled a thorough comparison of their effectiveness. The utilization of multiple evaluation criteria allowed for a nuanced understanding of each model's strengths and weaknesses, facilitating a more informed decision regarding their suitability for specific image classification challenges.

### 2.5 Performance Evaluation

After performing logistic regression and CNN-based models, the next step involves the assessment of their performance using various metrics such as accuracy, precision, recall, and F1-score. These metrics provide a comprehensive view of how well the models are performing in a classification task. Below is a description of the formulas used for these metrics:

**Accuracy:** Accuracy is a measure of how many predictions were correct out of the total number of predictions made. It is calculated using the formula:

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Accuracy=Number of Correct PredictionsTotal Number of PredictionsAccuracy=Total Number of PredictionsNumber of Correct Predictions

**Precision:** Precision quantifies the number of true positive predictions made by the model relative to all positive predictions. It is calculated as:

Precision=True PositivesTrue Positives + False PositivesPrecision=True Positives + False PositivesTrue Positives

**Recall:** Recall, also known as sensitivity or true positive rate, measures the number of true positive predictions made by the model relative to the total number of actual positive instances. It is calculated as:

Recall=True PositivesTrue Positives + False NegativesRecall=True Positives + False NegativesTrue Positives

**F1-Score:** The F1-score is the harmonic mean of precision and recall and provides a balanced measure of a model's performance. It is calculated as:

F1-Score=2·Precision·RecallPrecision + RecallF1-Score=Precision + Recall2·Precision·Recall

These metrics are essential in evaluating the effectiveness of machine learning models in classification tasks, providing insights into their strengths and weaknesses."

$$Accuracy = \frac{True\ Ppsotive + True\ Negative}{True\ Ppsotive + True\ Negative + False\ Positive + False\ Negative}$$

$$Precision = \frac{True\ Ppsotive}{True\ Positive + False\ Positive}$$

$$Recall = \frac{True\ Ppsotive}{True\ Ppsotive + False\ Positive}$$

$$F1 - Score = 2\frac{Precision - Recall}{Precision + Recall}$$

## III. RESULTS AND DISCUSSION

### 3.1 Generated Results using Logistic Regression

The outcomes gleaned from the evaluation subsequent to the implementation of logistic regression in the realm of image classification paint a picture of a model with rather constrained performance, as graphically illustrated in Fig. 2. The accuracy, residing at a mere 31.25%, casts light upon the model's ability to correctly classify only approximately one-third of the images within the dataset. This observation strongly hints at its struggle in effectively distinguishing between different classes, signifying room for substantial improvement in its classification capabilities.

Examining precision, which stands at a modest 33%, we deduce that among the positive predictions made by the model, roughly one-third were indeed accurate. While this statistic suggests that the model's positive predictions are not entirely unreliable, it raises questions about its ability to consistently provide dependable results.

Moreover, delving into the recall metric, which registers at 31%, it becomes apparent that the model could identify merely around 31% of all the actual positive instances present in the dataset. Given the crucial role recall plays in detecting true positives, this figure underscores a clear need for enhancement in capturing positive instances more comprehensively.

The F1-score, a holistic measure combining precision and recall, echoes the same sentiment with a rating of 31%. This score underscores the model's overall modest performance, reinforcing the notion that there exists ample room for refining and optimizing the logistic regression model for image classification purposes.

In light of these metrics and their collective implications, it becomes apparent that the logistic regression model may benefit significantly from further refinement and development to better meet the demands of image classification tasks.

```
Accuracy: 31.25%
Precision: 0.33
Recall: 0.31
F1-score: 0.31
```

Fig. 2. Results of the evaluation of logistic regression

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### 3.2 Generated Results using VGG16 with Logistic Regression

The outcomes derived from the assessment of the VGG16 model in conjunction with logistic regression for image classification unveil an encouraging glimpse into its capabilities, as elucidated in Figure 3. The attained accuracy rate of 84.58% serves as a testament to the model's proficiency in effectively categorizing a substantial majority of the images contained within the dataset. This achievement underscores the model's capacity to adeptly differentiate between various classes, positioning it as a valuable tool in the realm of image classification.

Delving deeper into the model's performance metrics, we find that its precision stands at an impressive 86%. This statistic signifies that the model's positive predictions are, with remarkable consistency, correct roughly 86% of the time. In essence, it excels in delivering accurate affirmative classifications, minimizing the occurrence of false positives, which is a pivotal characteristic for many practical applications.

In addition to precision, the recall rate of 85% is another noteworthy facet of the model's prowess. This metric reveals that the model successfully identified approximately 85% of all genuine positive instances within the dataset. This implies that it is proficient at recognizing and capturing the majority of relevant data points belonging to the classes of interest. High recall rates are especially crucial in scenarios where missing positive instances could lead to significant consequences.

The F1-score, a pivotal composite metric, further reinforces the model's commendable overall performance. With an F1-score of 85%, the model strikes an admirable balance between precision and recall. This score signifies that it harmoniously combines the ability to provide accurate positive predictions while simultaneously identifying a substantial portion of true positive instances. The F1-score's value serves as a compelling indicator of the model's robustness and effectiveness across the spectrum of image classification tasks, confirming its standing as a capable and reliable solution in this domain.

```
Accuracy: 84.58%
Precision: 0.86
Recall: 0.85
F1-score: 0.85
```

Fig. 3. Results of the evaluation of VGG16 with logistic regression

### 3.3 Summary of Evaluation

TABLE IIIII: Model comparison

| **Metrics** | **Logistic Regression** | **VGG16 with Logistic Regression** | **% Increase** |
|---|---|---|---|
| **Accuracy** | 31.25% | 84.58% | **53.33%** |
| **Precision** | 33% | 86% | **53%** |
| **Recall** | 31% | 85% | **54%** |
| **F1-score** | **31%** | **85%** | **54%** |

## IV. CONCLUSION

The study's findings regarding the application of logistic regression and the integration of VGG16 with logistic regression have produced distinct outcomes within the realm of image classification. The approach utilizing VGG16 has showcased a noteworthy improvement compared to the pure logistic regression model, demonstrating a substantial increase of 53.33% in accuracy, 53% in precision, 54% in recall, and an equally impressive 54% boost in the F1-score. These substantial enhancements underscore the effectiveness of incorporating deep learning techniques, exemplified by VGG16, into the realm of image classification tasks.

The substantial performance improvements observed across all key metrics highlight the potency of harnessing convolutional neural networks for feature extraction. This capability empowers the model to capture intricate patterns and nuances inherent in the image data. Consequently, this outcome underscores the advantage of embracing advanced techniques when confronting complex image classification challenges, where precision, recall, and overall accuracy hold paramount importance in achieving optimal results.

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