

Software Requirements Specification for ANN: Artificial Neural Network

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Revision History

Date	Version	Notes
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Feb. 14, 2024	1.1	Modification According to the Feedback
Feb. 16, 2024	1.2	Modification According to the Feedback 2
Apr. 8, 2024	1.3	Modification According to Dr. Smith's Feedback

1 Reference Material

This section records information for easy reference.

1.1 Table of Units

In this document, the unit of measurement used is the pixel (px), which is relevant for specifying image dimensions in image processing tasks. The pixel is a non-SI (custom) unit and is the only unit mentioned in this specification, as it directly relates to the digital images being classified in this project.

symbol	unit
px	pixel (matrix entity)

1.2 Table of Symbols

The table that follows summarizes the symbols used in this document along with their units. The choice of symbols was made to be consistent with Artificial Neural Network literature and with existing documentation for Image Classification. The symbols are listed in alphabetical order.

symbol	unit	description
α	—	Learning rate in gradient descent
a^L	—	Weighted input to neurons of layer L
b^L	—	Bias vector of layer L in neural networks
b_i^L	—	Bias of neuron i of layer L
∂	—	Partial derivation to represent the rate of change of a function with respect to one variable
∇	—	Gradient operator
σ	—	Activation function
$\sigma'(x)$	—	Derivation of σ function with x as the input of the function
W^L	—	Weight matrix of layer L in neural networks
w_{ij}^L	—	Weight between neuron i and neuron j of layer L
y_j	—	Target output for neuron j
z_i^L	—	Output of neuron i of layer L

1.3 Abbreviations and Acronyms

symbol	description
A	Assumption
DD	Data Definition
GD	General Definition
GS	Goal Statement
IM	Instance Model
LC	Likely Change
R	Requirement
SRS	Software Requirements Specification
ANN	Artificial Neural Newtwork for Image Classification
TM	Theoretical Model

1.4 Mathematical Notation

Typographic Conventions: In this document, matrices are denoted by uppercase letters (e.g., \mathbf{W} for weight matrices), vectors by lowercase letters (e.g., \mathbf{a} for activation vectors), and scalars by regular font (e.g., α for the learning rate). Greek letters are used for specific functions or parameters (e.g., σ for the activation function).

Symbols for Mathematical Operations:

- ∇ (nabla): Represents the gradient operator, used in gradient descent.
- Σ (sigma): Denotes summation.
- ∂ : Symbol for partial derivatives, indicating the rate of change of a function with respect to one of its variables while keeping other variables constant. It is extensively used in backpropagation algorithms for calculating gradients.

2 Introduction

The evolution of machine learning and its profound impact on various fields has led to remarkable advancements, particularly in the area of image classification. This project delves into the exploration of enhancing an Artificial Neural Network (ANN) to tackle the challenge of classifying images from the CIFAR-10 dataset [Krizhevsky \(2009\)](#). This dataset, known for its diverse range of images, serves as a crucial benchmark in assessing the capabilities of image recognition algorithms. Our goal is to not only improve the accuracy of the ANN but also to make it robust enough to handle all ten categories of the dataset effectively.

2.1 Purpose of Document

The primary purpose of this Software Requirements Specification (SRS) document is to clearly define the software requirements for the development of an advanced neural network model for image classification using the CIFAR-10 dataset. This document aims to provide a comprehensive understanding of the system, addressing various aspects such as the project's goals, theoretical underpinnings, and fundamental definitions. It maintains an abstract perspective, focusing on identifying and specifying what needs to be solved rather than delving into the technicalities of how these solutions will be implemented. The document will describe the system context and constraints, delineate the specific problem definition, and outline the requirements and characteristics of the proposed solution. Additionally, it will address potential changes and modifications that could impact the development of the neural network model.

2.2 Scope of Requirements

The scope of this project is specifically tailored to developing an enhanced neural network model for image classification using the CIFAR-10 dataset [Krizhevsky \(2009\)](#). This involves:

- **Model Complexity:** The project will concentrate on enhancing an existing ANN architecture. It will not venture into developing entirely new models from scratch or exploring unrelated AI domains like natural language processing.
- **Operational Boundaries:** The tool will be designed for a general-purpose computing environment, without tailoring for specialized hardware like high-performance GPU clusters.
- **Functional Focus:** The primary function is to improve classification accuracy and efficiency. Features outside the realm of image classification, such as real-time data processing or integration with external APIs, are outside the project's scope.
- **Image Specifications:** To further define the project's scope, it is essential to note that the system is tailored to process images containing only a single object. This focus allows for more precise and efficient classification within the specified dataset. Additionally, the system is optimized for handling images in PNG and JPEG formats, which are widely used and provide a good balance between image quality and file size.

For more details, you can also see the assumptions section (Section [4.2.1](#)).

2.3 Characteristics of Intended Reader

The intended readers for this project, which involves developing an enhanced neural network model for image classification using the CIFAR-10 dataset [Krizhevsky \(2009\)](#), are likely to be individuals with a solid background in computer science. Specifically, this refers to readers who have at least an undergraduate level of education in computer science or a related field. Ideal readers would have taken foundational courses such as Introduction to Computer Science, Data Structures, and Algorithms, and at least one introductory course in Machine Learning or Artificial Intelligence.

2.4 Organization of Document

The organization of this document is modeled on the SRS template for scientific computing software as outlined by [Smith and Lai \(2005\)](#). This approach systematically presents the system's objectives, theoretical underpinnings, definitions, and foundational assumptions. To facilitate a top-down reading approach, the readers can begin by reading the system's goal statements (Section 4.1.3). Following this, the theoretical models are detailed, which build upon and clarify the goals. The document concludes with instance models, providing readers with a comprehensive understanding of the system's practical applications and functionalities.

3 General System Description

This section provides general information about the system. It identifies the interfaces between the system and its environment, describes the user characteristics and lists the system constraints.

3.1 System Context

The system's context, as depicted in Figure 1, comprises three main elements: circles, a rectangle, and arrows. The circles symbolize the user who interacts with the software. The rectangle signifies the truss tool software system itself. Arrows in the diagram are used to illustrate the flow of data, showing both the input provided by the user and the output data generated by the system that is relevant and useful to the user. This setup provides a clear visual framework of the system's interaction dynamics.

- User Responsibilities:
 - Input correct and relevant data into the system for example not a text file
 - Upload images that are compatible with the system's specifications and within the scope of the CIFAR-10 dataset [Krizhevsky \(2009\)](#) classifications
- ANN Responsibilities:



Figure 1: System Context

- Detect data type mismatch, such as text file instead of an image
- Process image data, ensuring timely and accurate output
- Ensure the security and privacy of any data uploaded by users for classification

3.2 User Characteristics

The users of this image classification system are anticipated to have basic proficiency in using computer software, specifically comfortable with basic command line operations. This level of proficiency is suitable for individuals at an undergraduate level in computer science or related fields, or those with equivalent experience in a non-academic setting. Users should be familiar with navigating directories and entering commands in a command line interface (CLI) to upload images by specifying file paths. Their understanding of image classification should be fundamental, enough to set realistic expectations of the system’s functionality. While extensive expertise in machine learning is not required, a general familiarity with the types of images in the CIFAR-10 dataset [Krizhevsky \(2009\)](#) will be beneficial for choosing appropriate images for classification. Additionally, a keen interest or curiosity in the practical applications of machine learning, especially in areas like image classification, will likely enhance their experience and engagement with the system.

3.3 System Constraints

In this project, system constraints are critical as they shape the design space and specify how the system must integrate into the real world.

Technical Resource Limitations: The design accommodates typical computational resources, like processing power and memory, available to users. This limitation is an external constraint impacting the complexity and efficiency of the neural network model.

4 Specific System Description

This section first presents the problem description, which gives a high-level view of the problem to be solved. This is followed by the solution characteristics specification, which presents the assumptions, theories, definitions and finally

4.1 Problem Description

The ANN in this project is intended to solve the complex challenge of image classification, a task that involves correctly identifying the content of digital images. The problem arises from the need for a highly accurate, efficient, and reliable classification model that can navigate through the intricacies of image data, discerning subtle differences and patterns.

4.1.1 Terminology and Definitions

This subsection provides a list of terms that are used in the subsequent sections and their meaning, with the purpose of reducing ambiguity and making it easier to correctly understand the requirements:

- **Artificial Neural Network (ANN):** A computational model inspired by the human brain's network of neurons, used for tasks like image recognition and classification.
- **Image Classification:** The process of identifying and categorizing elements in a digital image into predefined classes.
- **CIFAR-10 Dataset [Krizhevsky \(2009\)](#):** A collection of images used for evaluating machine learning models, consisting of 60,000 32x32 color images in 10 different classes. These classes are: airplane, automobile, bird, cat, deer, dog, frog, horse, ship, and truck. More information is provided by University of Toronto on their website [HERE](#).
- **Accuracy:** In the context of an ANN, the degree to which the model correctly classifies test images.
- **Efficiency:** Refers to the computational performance of the ANN, including processing speed and resource utilization.
- **Reliability:** The consistency of the ANN's performance across various images with the same size (mxn) of training data.

4.1.2 System Components and Architecture Description

This ANN system is primarily software-based, focusing on computational processes and algorithms for image classification, and consequently, does not have a physical description in the traditional sense. Therefore, ANN consists of several key elements critical to its functionality:

- **Software Architecture:** Emphasizing a modular design to facilitate maintenance and scalability.
- **Data Processing Methods:** Involving algorithms and techniques for handling and preparing image data for classification.

- **User Interface Design:** Focused on user-friendliness and ease of interaction, particularly for uploading images and viewing results.
- **Performance Metrics:** Key indicators such as classification accuracy and processing speed are used to gauge system effectiveness.

These components are integral to the system's ability to perform its intended image classification tasks efficiently and accurately.

4.1.3 Goal Statements

Given the input image, the goal statements are:

GS1: Predict the class of the uploaded image

4.2 Solution Characteristics Specification

The instance models that govern ANN are presented in Subsection 4.2.6. The information to understand the meaning of the instance models and their derivation is also presented, so that the instance models can be verified.

4.2.1 Assumptions

This section simplifies the original problem and helps in developing the theoretical model by filling in the missing information for the physical system. The numbers given in the square brackets refer to the theoretical model [TM], general definition [GD], data definition [DD], instance model [IM], or likely change [LC], in which the respective assumption is used.

A1: All images are of a size of $m \times n$ based on the size of images of training data set

A2: The input image contains only one object

A3: Every uploaded image belongs to one of the 10 predefined classes (airplane, automobile, bird, cat, deer, dog, frog, horse, ship, truck) in the CIFAR-10 dataset [Krizhevsky \(2009\)](#)

4.2.2 Theoretical Models

This section focuses on the general equations and laws that ANN is based on.

RefName: TM:COE

Label: Cost Function

Equation: $\text{Cost} = \sum_{j=0}^{n_{L-1}} \left(a_j^{(L)} - y_j \right)^2$

Description: In this project the cost function is sum of squared errors (SSE). Our goal is to minimize cost function.

$a_j^{(L)}$: Predicted value for the j-th output in the training data.

n_{L-1} : Number of neurons in the neural network's penultimate layer.

y_j : Actual value for the j-th output in the training data.

Notes: None.

Source: [Wikipedia contributors \(2024b\)](#)

Ref. By: GD1

Preconditions for TM:COE: None

Derivation for TM:COE: Not Applicable

4.2.3 General Definitions

This section collects the laws and equations that will be used in building the instance models.

Number	GD1
Label	Gradient Descent
SI Units	-
Equation	$(W, b)_{new} = (W, b)_{old} - \alpha \nabla \text{Cost}$
Description	In this project, Gradient Descent is a method used to minimize the cost function, essential for improving the neural network's accuracy. It adjusts the weights (W) and biases (b) of the network by subtracting a fraction (represented by the learning rate α) of the cost function's gradient (∇Cost) from the current values.
Source	Wikipedia contributors (2024a)
Ref. By	IM1

Detailed derivation of simplified rate of change of temperature

For updating the weights matrices and bias vectors using Gradient Descent, it is needed to first find the ∇Cost . For this purpose, it is needed to find the partial derivative of weights and biases. The chain rule is applied to find the desired partial derivatives:

- **Last Layer Derivations:**

- Weight: $\frac{\partial \text{Cost}}{\partial w_{jk}^{(L)}} = \frac{\partial \text{Cost}}{\partial a_j^{(L)}} \times \frac{\partial a_j^{(L)}}{\partial z_j^{(L)}} \times \frac{\partial z_j^{(L)}}{\partial w_{jk}^{(L)}} = 2(a_j^{(L)} - y_j) \times \sigma'(z_j^{(L)}) \times a_k^{(L-1)}$
- Bias: $\frac{\partial \text{Cost}}{\partial b_j^{(L)}} = \frac{\partial \text{Cost}}{\partial a_j^{(L)}} \times \frac{\partial a_j^{(L)}}{\partial z_j^{(L)}} \times \frac{\partial z_j^{(L)}}{\partial b_j^{(L)}} = 2(a_j^{(L)} - y_j) \times \sigma'(z_j^{(L)}) \times 1$
- Activation: $\frac{\partial \text{Cost}}{\partial a_k^{(L-1)}} = \sum_{j=0}^{n_{L-1}} \left(\frac{\partial \text{Cost}}{\partial a_j^{(L)}} \times \frac{\partial a_j^{(L)}}{\partial z_j^{(L)}} \times \frac{\partial z_j^{(L)}}{\partial a_k^{(L-1)}} \right)$

- **Other Layers Derivations:**

- Weight: $\frac{\partial \text{Cost}}{\partial w_{km}^{(L-1)}} = \frac{\partial \text{Cost}}{\partial a_k^{(L-1)}} \times \sigma'(z_k^{(L-1)}) \times a_m^{(L-2)}$
- Bias: $\frac{\partial \text{Cost}}{\partial b_k^{(L-1)}} = \frac{\partial \text{Cost}}{\partial a_k^{(L-1)}} \times \sigma'(z_k^{(L-1)}) \times 1$
- Activation: $\frac{\partial \text{Cost}}{\partial a_m^{(L-2)}} = \sum_{k=0}^{n_{L-2}} \left(\frac{\partial \text{Cost}}{\partial a_k^{(L-1)}} \times \sigma'(z_k^{(L-1)}) \times w_{km}^{(L-1)} \right)$

j : This index represents a specific neuron in the current layer. It's used to refer to each individual output neuron in the last layer of the network.

k : This index is used to refer to neurons in the layer preceding (L-1) the current one. It's involved in calculations that connect the neurons of two consecutive layers.

m : The index m is used to refer to neurons or inputs from an earlier layer than k , indicating the propagation of influence from one layer to another in the neural network.

These derivations represent how the partial derivatives of the cost function with respect to the weights, biases, and activations are computed using the chain rule. For the last layer, these derivations are direct and involve the actual outputs of the network compared to the target values, which directly contribute to the cost. In other layers, the derivatives are computed as a sum over all neurons in the subsequent layer because each neuron's activation in layer L-1 contributes to the activations in layer L, thus indirectly affecting the cost. This approach ensures that the adjustments made to weights and biases through gradient descent are based on how much they contribute to the overall error in the network's predictions.

4.2.4 Data Definitions

This section collects and defines all the data needed to build the instance models. The dimension of each quantity is also given. In our model, we process RGB images, which are represented as three-dimensional (3D) matrices. However, each color channel (Red, Green, and Blue) in an RGB image is individually represented by a two-dimensional (2D) matrix. Therefore, an RGB image comprises three 2D matrices, one for each color channel, collectively forming a 3D matrix structure.

4.2.5 Data Types

This section collects and defines all the data types needed to document the models.

As outlined in the Data Definition section (Section 4.2.4), our project primarily uses images represented as 3D matrices. These matrices are comprised of numerical data, which includes pixel values of the images. This numerical aspect is fundamental for the processing and interpretation tasks the neural network undertakes, ensuring accurate image analysis and classification.

Type Name	Image
Type Symbol	img
Type Def	3D matrix of numerical data
Description	Images are represented as 3D matrices, with each matrix element corresponding to pixel values across Red, Green, and Blue color channels. Each pixel is a natural number, with a value between 0 and 255.

4.2.6 Instance Models

This section transforms the problem defined in Section 4.1 into one which is expressed in mathematical terms. It uses concrete symbols defined in Section 4.2.4 to replace the abstract symbols in the models identified in Sections 4.2.2 and 4.2.3.

The goals GS1 are solved by IM1.

Instance Model 1

Number	IM1
Label	Feedforward to find $a^{(L+1)}$
Input	Raw pixel values of an image
Output	The predicted class of the input image using $a^{(L+1)} = \sigma(W^{(L+1)}a^{(L)} + b^{(L+1)})$, $W^{(L+1)}$ and $b^{(L+1)}$ from GS1
Description	<p>The feedforward process in neural networks involves input data propagation to output prediction or classification. This includes calculating weighted sums and biases in each layer, followed by an activation function. Network weights are initially set using random normal distributions, and biases start as zero vectors. These initial settings are crucial as they impact the network's learning and evolution during training. After each iteration the result of this part will be used to update the weights and biases.</p> <p>$a^{(L)}$: Output activations of the L-th layer in a neural network.</p> <p>$a^{(L+1)}$: Activations for the next layer, (L+1), resulting from the current layer's output.</p> <p>σ (sigma): The activation function applied to layer outputs, influencing neuron firing.</p> <p>$b^{(L+1)}$: Bias vector for the (L+1)-th layer, adjusting neuron activation thresholds.</p> <p>$W^{(L+1)}$: Weight matrix connecting layer L to layer (L+1), essential for learning patterns.</p>
Sources	Wikipedia contributors (2024a)
Ref. By	GS1

4.2.7 Input Data Constraints

Table 1 shows the data constraints on the input output variables. The column for physical constraints gives the physical limitations on the range of values that can be taken by the variable. The column for software constraints restricts the range of inputs to reasonable values. The software constraints will be helpful in the design stage for picking suitable values.

algorithms. The constraints are conservative, to give the user of the model the flexibility to experiment with unusual situations. The column of typical values is intended to provide a feel for a common scenario. The uncertainty column provides an estimate of the confidence with which the physical quantities can be measured. This information would be part of the input if one were performing an uncertainty quantification exercise.

Table 1: Input Variables

Var	Physical Constraints	Software Constraints	Typical Value	Uncertainty
img format	None	Acceptable formats	PNG or JPG	None
img height	m	Input data height	Training data height	None
img width	n	Input data width	Training data width	None

5 Requirements

This section provides the functional requirements, the business tasks that the software is expected to complete, and the nonfunctional requirements, the qualities that the software is expected to exhibit.

5.1 Functional Requirements

- R1: The system requires user-uploaded images in a specified format and resolution as is mentioned in the Table 1..
- R2: Verify the given inputs are in correct form and satisfy the required physical constraints given in the Table 1, by checking the type of the input file and if it is acceptable then by checking the size of the image. The system provides feedback by displaying the classification results for user confirmation.
- R3: Classify the uploaded image from IM1.

5.2 Nonfunctional Requirements

- NFR1: **Accuracy** The system aims for higher classification accuracy than [previous model](#), measurable through defined quantitative methods.
- NFR2: **Usability** The system should be user-friendly the way that everything is so clear and well explained for the users. Also, this will be easy to navigate for users with varying levels of technical expertise.

NFR3: **Maintainability** The software should be easy to modify. This is designed for easy maintainability, emphasizing modular architecture, following coding standards, comprehensive documentation, and robust testing practices. These factors ensure efficient updates, adaptations, and debugging, facilitating straightforward modifications and reducing long-term maintenance efforts.

NFR4: **Portability** The system is compatible with multiple operating environment, including Windows and macOS.

NFR5: **User Interaction Efficiency** The system allowws users to easily upload images and view classification results with minimal complexity and effort, ensuring a smooth and user-friendly experience.

NFR6: **Accuracy and Validation** The system will provide its classification results based on the trained model, acknowledging that accuracy may not be 100%. To validate outputs, the system will incorporate a user feedback mechanism.

NFR7: **User-Friendly Output Presentation** The system presents classification results in an understandable format, clearly indicating the identified image categories.

5.3 Rationale

In this Section, we delve into the reasoning behind key decisions in our documentation. The scope was specifically chosen to focus on the CIFAR-10 dataset [Krizhevsky \(2009\)](#), targeting a manageable yet diverse range of image classifications to demonstrate the neural network's capabilities effectively. Our modeling choices, including the neural network architecture and algorithms like gradient descent, were selected for their proven effectiveness and relevance to the image classification task at hand. Assumptions were made based on realistic scenarios and limitations, ensuring that our model remains practical and applicable. The typical values chosen, such as image dimensions and parameter settings, were guided by standard practices in the field and the specifics of the CIFAR-10 dataset [Krizhevsky \(2009\)](#), aiming to optimize the model's performance and accuracy. Each decision was made with careful consideration of its impact on the project's objectives and feasibility.

6 Likely Changes

LC1: [A2](#) The system might be changed to evolve to identify multiple objects within a single image, enhancing its complexity and usability.

LC2: [A3](#) The system can be trained on larger dataset, such as CIFAR-100 [Krizhevsky \(2009\)](#), to be able to classify more objects.

7 Unlikely Changes

LC3: A1 The model architecture depends on the size of the training dataset. Consequently, the size of uploaded images should be always compatible with the size of training dataset.

8 Traceability Matrices and Graphs

The purpose of the traceability matrices is to provide easy references on what has to be additionally modified if a certain component is changed. Every time a component is changed, the items in the column of that component that are marked with an “X” may have to be modified as well. Table 2 shows the dependencies of theoretical models, general definitions, data definitions, and instance models with each other. Table 3 shows the dependencies of instance models, requirements, and data constraints on each other. Table 4 shows the dependencies of theoretical models, general definitions, data definitions, instance models, and likely changes on the assumptions.

	TM:COE	GD1	IM1
TM:COE		X	
GD1	X		X
IM1		X	

Table 2: Traceability Matrix Showing the Connections Between Items of Different Sections

	IM1	4.2.7	R1	R2	R3
IM1					X
R1					
R2		X			
R3		X			

Table 3: Traceability Matrix Showing the Connections Between Requirements and Instance Models

The purpose of the traceability graphs is also to provide easy references on what has to be additionally modified if a certain component is changed. The arrows in the graphs represent dependencies. The component at the tail of an arrow is depended on by the component at the head of that arrow. Therefore, if a component is changed, the components that it points to should also be changed.

	A1	A2	A3
TM:COE	X		X
GD1	X		
IM1	X		
LC1		X	
LC2			X

Table 4: Traceability Matrix Showing the Connections Between Assumptions and Other Items

9 Development Plan

In this section, we outline our approach to building the software. The plan is divided into phases, prioritizing core functionalities first.

- **Phase1:** Initial development focuses on basic functionalities like image uploading and primary classification training using the CIFAR-10 dataset [Krizhevsky \(2009\)](#). This phase ensures the system’s ability to categorize images correctly.
- **Phase2:** The aim is to enhance the model’s accuracy and efficiency. However, the extent of improvement will be explored during the development process, as we experiment with algorithm optimizations and neural network architectures.
- **For Coursework:** The primary goal within the course is to establish the foundational image classification functionality (Phase 1), while efforts to enhance accuracy (Phase 2) will be attempted but are subject to the scope and limitations of the coursework.

10 Values of Auxiliary Constants

The following are the values for the symbolic parameters used throughout this report:

- **Image Dimensions (mxn):** 32x32 (Standard dimensions of images in the CIFAR-10 dataset [Krizhevsky \(2009\)](#).)

These values are set here for ease of maintenance and to ensure consistency across the report.

References

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