

# BLIND IMAGE QUALITY ASSESSEMENT MODEL BASED ON MULTI-TASK LEARNING

NORZAWANI BINTI AB KHALID

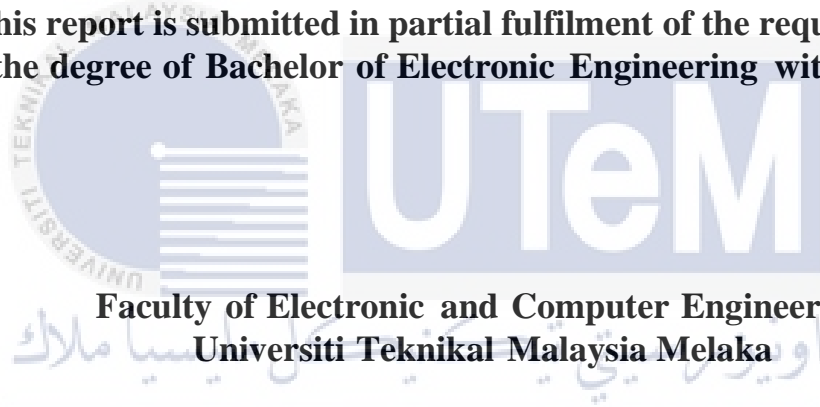


UNIVERSITI TEKNIKAL MALAYSIA MELAKA

**BLIND IMAGE QUALITY ASSESSEMENT MODEL BASED  
ON MULTI-TASK LEARNING**

**NORZAWANI BINTI AB KHALID**

**This report is submitted in partial fulfilment of the requirements  
for the degree of Bachelor of Electronic Engineering with Honours**



**Faculty of Electronic and Computer Engineering  
Universiti Teknikal Malaysia Melaka**

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**BORANG PENGESAHAN STATUS LAPORAN**  
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## DECLARATION

I declare that this report entitled “Blind Image Quality Assessment Model Based on Multi-Task Learning” is the result of my own work except for quotes as cited in the references.



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## APPROVAL

I hereby declare that I have read this report and in my opinion this report is sufficient in terms of scope and quality for the award of Bachelor of Electronic Engineering with Honours.



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## DEDICATION

I dedicate this report to my supervisor Dr Redzuan bin Abdul Manap, my beloved family and all my friends.



## ABSTRACT

The project focuses on an image quality assessment (IQA) model that estimates the quality of an image without the presence of reference information. Current blind IQA (BIQA) models typically learn their prediction separately for different image distortions, ignoring the relationship between the learning tasks. As a result, a BIQA model may have great prediction performance for images affected by one particular type of distortion but is less effective when tested on others. This project aims to address this limitation by training a new BIQA model simultaneously under different distortion conditions using a multi-task learning (MTL) technique. Given a set of training images, the model will first extract spatial domain BIQA features. The features will then use as an input to an MTL framework to simultaneously learn prediction models for different distortion classes. The predicted quality scores from each distortion class are to be weighted by the probability estimates of each distortion present in the image to yield the overall image quality score

## ABSTRAK

Projek ini memberi tumpuan kepada model penilaian kualiti imej (IQA) yang menganggarkan kualiti imej tanpa kehadiran maklumat rujukan. Model IQA tanpa rujukan (BIQA) biasanya mempelajari ramalan mereka secara berasingan untuk herotan imej yang berbeza di mana hubungan antara tugas pembelajaran diabaikan. Ini menyebabkan model BIQA mungkin menghasilkan prestasi ramalan yang baik untuk imej yang terjejas oleh satu jenis herotan tetapi kurang berkesan apabila diuji dengan herotan yang lain. Projek ini bertujuan untuk menangani kelemahan ini dengan melatih satu model BIQA baharu di bawah pelbagai herotan yang berbeza secara serentak menggunakan teknik pembelajaran pelbagai tugas (MTL). Diberi satu set imej latihan, model ini akan mengekstrak terlebih dahulu ciri BIQA dalam domain spatial. Ciri tersebut kemudiannya akan digunakan sebagai input kepada rangka kerja MTL untuk mempelajari model ramalan secara serentak bagi kelas herotan yang berbeza. Skor kualiti yang diramalkan daripada setiap kelas herotan kemudiannya diberi pemberat iaitu anggaran kebarangkalian setiap herotan yang terdapat dalam imej untuk menghasilkan skor kualiti keseluruhan imej tersebut.



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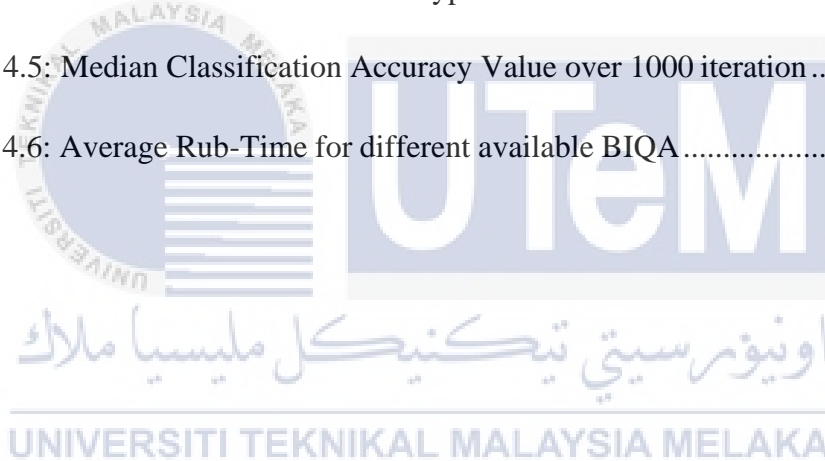
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## LIST OF SYMBOLS AND ABBREVIATIONS

BIQA	:	Blind images quality assessment
BIQI	:	Blind Image Quality Index
BRISQUE	:	Blind/Reference-less Image Spatial Quality Evaluator
CNN	:	Convolution Neural Network
CORNIA	:	Codebook Representation for No-reference Image Assessment
DCT	:	Discrete Cosine Transformation
DMOS	:	Difference Mean Opinion Score
DS	:	Distortion-Specific
DNN	:	Deep Neural Network
FRIQA	:	Full Reference Image quality assessment
GDN	:	Google Display Network
GM	:	Gradient Magnitude
IQA	:	Image Quality Assessment
JPEG	:	Joint Photographic Experts Group
LCC	:	Linear Cross Correlation
LOG	:	Laplacian of Gaussian
MOS	:	Mean Opinion Score
MTL	:	Multi-Task Learning



MEON	:	Multi-Task End-To-End Optimized Deep Neural Network
MSE	:	Mean Square Error
NSS	:	Natural Scene Statistic
NRIQA	:	No Reference Image Quality Assessment
PSNR	:	Peak Signal-to-Noise Ratio
QOE	:	Quality of Experience
RAM	:	Random Access Memory
ROI	:	Region of Interest
RMSE	:	Root Mean Square Error
SROCC	:	Spearman Rank-order Cross Correlation
SIANN	:	Space Invariant Artificial Neural Networks
SVR	:	Support Vector Regression
SVM	:	Support Vector Machine
STL	:	Single-Task Learning
WN	:	White Noise

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# CHAPTER 1

## INTRODUCTION



### 1.1 Introduction

Latterly, research interest on Image Quality Assessment (IQA) has increased interest owed to its wide application in image or video manufacturing. The quality assessment of outcomes result portrays a significant part in several image/videos' processors and machine learning tools. Many methods for assessing the quality of perceptual images have been discovered. Still, researchers must continue to improve technique in assessing image quality so that final users can obtain a satisfactory quality of experience (QoE).

IQA is a procedure to assess the presentation of image perception, a genuine index is used where it must be very consistent with the subjective index by humans. The human ratings are known to be as the ultimate standard in IQA.

These human ratings are typically derived through procedures in which humans are required to examine and improve the performance of original images shown to them depending on the scores provided. The ratings across all the participants are then averaged to achieve mean opinion score (MOS) or average opinion value difference (DMOS). The measure indicates the assessment methods used to analyse the image. However, this method is time-consuming and costly, and it cannot be carried out in real - world applications. Objective IQA models that can automatically provide quality measurements coherent with MOS / DMOS values are more convenient.

There are two major types of objective IQA: full-reference IQA (FR-IQA) and blind IQA (BIQA). FR-IQA models evaluate the whole information between the reference image and its image forecasting the performance of a distorted natural image. A reference image is a corresponding image that is free of distortion and of high quality. The most straightforward FR-IQA metrics are peak signal-to-noise ratio (PSNR) and mean squared error (MSE). However, they have been shown to have a limited association with human perceptual measures.

There are two types of BIQA models [1]: distortion-specific (DS) models and general-purpose models. DS BIQA techniques operate by implementing individual distortion model. Assuming that the distortion impacting the image is known from the beginning. For example, the method assumes the quality of JPEG compressed images in [2], while the quality of a motion-blurred raw image is tested blindly in [3]. The impact of blockage and noise objects are evaluated in [4] and [5], respectively. In contrast, in general-purpose BIQA models, no prior knowledge of the picture distortion is necessary. Instead, picture quality is examined to see how much the image is distorted in the same way that an image database is affected. Standard IQA databases

such as the LIVE [6] and the CSIQ [7] can be used as image exemplars. The models are then trained to estimate the MOS / DMOS of the image using such great examples and their provided MOS / DMOS values.

## 1.2 Problem Statement

Current BIQA models typically learn their prediction separately for different image distortions, ignoring the relationship between the learning tasks. As a result, a BIQA model may have great prediction performance for images affected by one particular type of distortion but is less effective when tested on others. A new model that can utilize the relationship between its learning new task under different distortion is highly desired.

## 1.3 Objective

The project aims to develop a new model by studying a new framework that can enable the model to be trained simultaneously under various distortion scenarios. This can be achieved by fulfilling the following objectives based on the stages of the project:

- 1) First, to extract relevant quality predictive spatial domain image features.
- 2) Employ MTL technique to simultaneously train the model for different image distortion classes.
- 3) To produce quality score based on MTL model prediction for different distortion class.
- 4) To analyze the model's performance through comparison with several available BIQA models in terms of prediction accuracy, generalization capability, and computational requirements.

#### 1.4 Scope of Work

The aim of this project is to develop the BIQA model. The FR-IQA and RR-IQA models will not be covered in this project. This model proposes to utilize IQA features that are based on Natural Scene Statistic (NSS). The model's feature is developed by extracting image data in the spatial domain. These features are derived from the combination of statistical properties of GM and LOG operators with the normalized luminance of an image without the need to undergo a transformation process. These characteristics then are applied to simultaneously learn regression models for various distortion scenarios. A trace-norm regularization MTL approach is used for the training whereby the model chooses a certain regression method for estimating the quality score of an image given a specified distortion. The model uses a support vector machine (SVM) classifier to estimate separate images' different distortions with an unknown distortion. The classification model's probability estimations are used to weight the picture evaluating scores of several regression models. The ultimate quality score is calculated by combining the weighted scores. For the performance evaluation, the training and the testing of the model are conducted using images from the LIVE Database.

## 1.5 Thesis Layout

This study contains of five chapters. Chapter 1 contains the preface of the project. It introduced the research area that needs to be studied, IQA. The previous IQA models are analyse and their limitation are identified, which leads to this project's objectives. Based on objectives, the project scope is determined.

Chapter 2 consists of brief background study on methods and approaches that have been used in designing current BIQA models. This chapter also discusses the limitations of the models, and a summary of these model are stated at the end of this chapter.

Chapter 3 explains the approaches used in the project execution. The implementation movement is described in detail which include several stages such as features extraction, regression for the BIQA model, model testing, and model's performance evaluation.

Chapter 4 consists of the observation recorded during the project development phase. The results obtained during experiments are presented, analysed and evaluated.

Chapter 5 summaries the findings based on the project's outcome, followed by the recommendations that can be implemented to enhance the project in the future.

## CHAPTER 2

### BACKGROUND STUDY



#### 2.1 Introduction

The background study for this project is based on several resources such as research journals, conference paper and previous thesis to gain more information and appropriate knowledge about the IQA. The theory of IQA and other model approaches that have been previously developed before are being used as guidance for this project. The overview, which focused on general-purpose models related to the work, are presented in this chapter. These models fall into two parts which are the NSS based models and the learning-based models. There are two major groups for NSS based models, which are transform-based approach models and transform-free approach models.