

# Design and Development of Semi-Automatic Tire Inspection Machine

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## DECLARATION

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I declare that this is my own work and this dissertation does not incorporate without acknowledgement any material previously submitted for a Degree or Diploma in any other University or institute of higher learning and to the best of my knowledge and belief it does not contain any material previously published or written by another person except where the acknowledgement is made in the text.

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## Abstract

Machine learning has become an important and interesting field when addressing complex industrial tasks. In this study, a semi-automatic tire inspection machine for tire retreading industry which uses machine learning techniques is developed.

Most consumers tend to retread their tires because retreading is an economical and an eco-friendly method. As a result, retreading industry is now becoming popular in developed countries as well as developing countries. Initial inspection is the most crucial activity in the retreading process because tire defect identification is performed in this phase. Failure in identification of defects prior to retreading, may cause delamination of a retreaded tire consequently leading to a disastrous accident.

There exist many advanced machines for initial tire inspection. Widely used method in the tire retreading industry is nondestructive defect detection based on X-Ray image processing. This method is very expensive and used by brand new tire manufacturing companies as well as tire retreading companies in developed countries. In addition to that, devices with holography and shearography techniques are used to identify defects which map the tire defects using optical means and are known to be extremely expensive.

Conventional inspection method is being followed by the Sri Lankan tire retreading industry as well as other developing countries such as India, Bangladesh etc. due to its cost effectiveness in replace of extremely expensive advanced machinery. The two main tasks performed in conventional inspection method are visual inspection and hammering test.

Operator carefully observe the worn tire, identify and mark the defects which could be observed through the naked eye under visual inspection. The identified defects can be classified as tire punctures, unwanted metal particles, ply damages, bead damages and side wall damages. Hammering test is carried out to identify the defects which are invisible to naked eye such as inner ply separations, ply damages of a tire, inner canvas damage and small air bubbles in tread area etc. Usually the test is performed by hammering all over the tire tread area using a brass rod and listening to the resulted noise difference by an expertise.

An expert human inspector performs both visual inspection and hammering test. This manual inspection is often associated with inaccurate results and undetected defects due to lack of expertise, causing visual fatigue which results in low efficiency and higher amount of labor costs in local tire retreading industry. Therefore, the main objective of this study is to eliminate the expert human resource from the initial tire inspection process and reduce the complexity of the activity.

In this research, visual inspection activity is trained to a model and Faster RCNN Inception v2 algorithm is used on TensorFlow platform. Image classification and tire defect detection are done with a collection of real-world industrial image data set. These images were captured using four cameras which were having a capacity of 12 mega pixels each. Basically 220 images were trained using a computer. Hammering test activity is trained to a model and YouTube-8M algorithm is used with VGGish

feature extractor on TensorFlow platform. The sound signal was captured via a normal USB microphone. The sound signal was analysed using Audacity open source software and fed as the input to train the model. Unwanted metal particles of the worn tires are detected using a metal detector. In addition to defect identification mechanisms, defect localisation system is developed using a microcontroller and an encoder. Defects which are identified from image processing or sound signal processing or metal detection, location of the defect is identified with respect to a reference point of tire. This is very useful for identifying the exact defect location of tire for the operator.

From the obtained results it can be concluded that, the above image classification and sound signal classification models provide results with a higher level of accuracy. Therefore, the expertise labor which is used to perform the initial inspection process could be replaced by a novice employee. Furthermore the unique and ideal structure of this developed machine is associated with low maintenance cost. As a result, small scale companies would be more comfortable with their existing financial situations when using this semi-automatic tire inspection machine to enhance their throughput of the tire retreading process.

***Keywords-*** tire retreading, object detection, sound classification, image processing, deep learning, machine learning, TensorFlow

## DEDICATION

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This dissertation is dedicated to my wife and parents, to whom I can trace my every success to.

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