



Development Of An Elephant Detection And Repellent System Based On EfficientDet-Lite models

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I certify that I have read this thesis and that in my opinion it is fully adequate, in scope and in quality, as a thesis for the degree of Master of Science.

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DECLARATION

I declare that this is my own research proposal, and this proposal does not incorporate without acknowledgement any material previously published 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

Human-elephant conflict (HEC) has become a major concern in Sri Lanka that results in many unfortunate human and elephant deaths. Methods that are currently in place to mitigate HEC, such as electrical fences have undesirable consequences resulting in both human and elephant casualties. In this paper, we have proposed a method based on computer vision and deep learning that has promising potential for detecting and repelling elephants without endangering the lives of elephants or humans. We have used EfficientDet-Lite models that provide a good compromise between accuracy and performance to be usable with a resource-constrained device like a Raspberry Pi.

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