



Ellipsoidal Coverage Function (ECF) – a Modified Mahalanobis Radial Basis Function with Geometrical Coverage Learning (GCL) Algorithm

Tanat Piumsuwan^{1*}, and Prompong Sugunnasil²

¹ Faculty of Engineering, Chiang Mai University, 50200, Thailand

² DAKSH Research Group, Chiang Mai University, 50200, Thailand

* Correspondence: tanat_pi@cmu.ac.th

Citation:

Piumsuwan, T.; Sugunnasil, P. Ellipsoidal coverage function (ECF) – a modified mahalanobis radial basis function with geometrical coverage learning (GCL) algorithm. *ASEAN J. Sci. Tech. Report.* **2026**, *29*(2), e259894. <https://doi.org/10.55164/ajstr.v29i2.259894>.

Article history:

Received: July 14, 2025

Revised: October 9, 2025

Accepted: November 15, 2025

Available online: January 21, 2026

Publisher's Note:

This article is published and distributed under the terms of the Thaksin University.

Abstract: This research presents an Ellipsoidal Coverage Function (ECF) with the addition of the Geometrical Coverage Learning (GCL) algorithm concept for classification. The motivation for this research stems from inefficiencies in nonlinear Deep Neural Networks (DNNs). The implementation of a higher-order function for neurons, while less popular than a deeper linear design, has been claimed to improve the robustness of the model in dealing with noisy environments and to negate the need for a deeper network. The ECF is a higher-order neuron design based on the Mahalanobis distance Radial Basis Function (MRBF) design, but with the number of parameters linearly scaled instead of quadratically with respect to the input dimension. This means that the ECF neuron can approximate the volume coverage of an MRBF in the feature space under a non-rotating constraint and is more suitable for integration into a neural network for further backpropagation (BP) optimization. The integration of the GCL into the ECF for classification architectures boosts learning efficiency, underscoring the versatility and potential impact of this research. The results from experiments with computer vision tasks in a transfer learning environment suggest that the integrated GCL ensures that the ECF can map all the data and correct the training parameters of the network faster. Furthermore, the ECF with the GCL algorithm demonstrates competitive performance relative to other nonlinear neuron designs in a transfer learning setup across different datasets, including itself without GCL. These findings point to a better nonlinear machine learning model in terms of performance and efficiency combined.

Keywords: Machine learning; deep learning; nonlinear neuron; artificial neural networks; smart initialization

1. Introduction

Deep Neural Networks (DNNs) have become the focus of machine learning research in the past few years. This is mainly due to their scalability, performance in various tasks (including natural language processing (NLP) and computer vision), and the availability of more capable hardware. DNNs can map complex structures and have been applied to both classification and clustering tasks [1, 2]. However, the field lacks major developments in terms of the fundamental structure, mainly the neuronal models and their training paradigms. The most well-known neuron is the McCulloch and Pitts (M-P) neuron, introduced in 1943 [3]. Since then, artificial neural networks have been