**A PROJECT REPORT**

**on**

**NEURO FUZZY CLASSIFICATION FOR DATA MINING TASKS**

**Submitted to**

**KIIT Deemed to be University**

**In Partial Fulfillment of the Requirement for the Award of**

**BACHELOR’S DEGREE IN**

**COMPUTER SCIENCE & ENGINEERING**

**By**

**SHALINI JAISWAL 1505062**

**PRIYANKA MAHATO 1505049**

**UNDER THE GUIDANCE OF**

**PROF. HIMANSU DAS**

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**SCHOOL OF COMPUTER ENGINEERING**

**KALINGA INSTITUTE OF INDUSTRIAL TECHNOLOGY**

**BHUBANESWAR, ODISHA - 751024**

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School of Computer Engineering

Bhubaneswar, Odisha 751024



**CERTIFICATE**

This is certify that the project entitled

**NEURO FUZZY CLASSIFICATION FOR DATA MINING TASKS**

Submitted By

SHALINI JAISWAL 1505062

PRIYANKA MAHATO 1505049

is a record of bonafide work carried out by them, in the partial fulfillment of the requirement for the award of Degree of Bachelor of Engineering (Computer Science & Engineering) at KIIT Deemed to be university, Bhubaneswar. This work is done during year 2018-2019, under our guidance.

Date: / /

**Prof.Himansu Das**

Project Guide

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**ABSTRACT**

Artificial Neural Network is a popularly used Machine Learning Algorithm both in research and industry.But the output of ANN fluctuates in a large range,to overcome this defect fuzzy logic is used to increase the number of feature and calculate the contribution of each feature in each class this helps in increasing consistency and accuracy especially for datasets that are not very large.

One of the shortcomings of Fuzzy Logic is that it is very time consuming so feature reduction techniques such as Principal Component Analysis ,Linear Discriminant Analysis and Independent Component Analysis is used and the results are recorded.

Finally feature selection algorithm called Differential Evolution algorithm is also used and the a comparative study is performed.

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