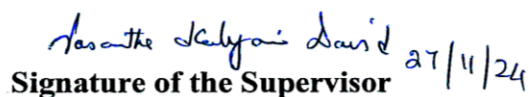


CERTIFICATE FROM THE SUPERVISOR

I certify that the thesis entitled “**Prediction of Heart Diseases Risk using Novel Machine Learning Techniques**” submitted for the award of Doctor of Philosophy (Ph.D.) by **Ms. Anuradha.P** is the record of research work carried out by her during the period from July 2017 to November 2024 under my guidance and supervision, and that this work has not formed the basis for the award of any Degree, Diploma, Associateship, Fellowship or other Titles in this Institute or any other University or Institution of Higher Learning.

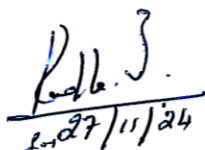

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Signature of the Head of the Department


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Signature of the Supervisor

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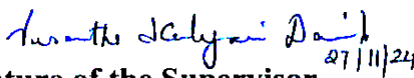

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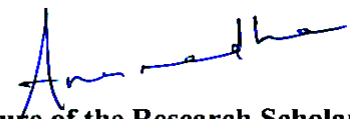
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DECLARATION

I declare that the thesis entitled “**Prediction of Heart Diseases Risk using Novel Machine Learning Techniques**” submitted by me for the award of Doctor of Philosophy (Ph.D.) is the record of work carried out by me during the period from July 2017 to November 2024 under the guidance of **Dr. (Mrs).Vasantha Kalyani David** and has not formed the basis for the award of any Degree, Diploma, Associateship, Fellowship, Titles in this Institute or any other University or other similar institution of Higher Learning.


Signature of the Supervisor ^{27/11/24}


Signature of the Research Scholar

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LIST OF ABBRIVATION

ACE	Angiotensin-converting enzyme
ACO	Ant Colony Optimization
AD	Alzheimer's Disease
ADNI	Alzheimer's Disease Neuroimaging Initiative
AI	Artificial Intelligence
AMI	Acute Myocardial Infraction
ANN	Artificial Neural Network
Bagging	Bootstrap Aggregating
BAR	BoostARoota
BAR-CB	BAR with CatBoost
BC	Breast Cancer
BCPS	BC prediction system
BDE	Binary Differential Evolution
BGWO	Binary Grey Wolf Optimization
BHO	Black Hole Optimization
BNP	Brain Natriuretic Peptide
BPSO	Binary Particle Swarm Optimization
CAD	Coronary Artery Disease
CatB	CatBoost
CBC	CatBoost Classifier
CFS	Correlation Based Feature Selection
CHI	chi-square
CKMB	Creatine Kinase Myocardial Band
COPD	Chronic Obstructive Pulmonary Disease
CS	Chi Square
CV	cross-validation
DBSCAN	Density-Based Spatial Clustering of Applications with Noise

DCT	Discrete Cosine Transform
DR	Dimensionality Reduction
DT	Decision Tree
ECG	Electrocardiogram
Eclat	Equivalence Class Transformation
EM	Expectation-Maximization
ETT	Exercise Tolerance Test
FCBF	Fast Correlation-Based Feature Selection
FI	Feature Importance
FOA	Firefly Optimization Algorithm
FP-growth	Frequent Pattern-growth
FS	Feature Score
GA	Genetic Algorithm
GA-CNN	Genetic Algorithm and Convolutional Neural Networks
GA-SAE	Genetic Algorithm and Stacked Autoencoder
GASEN	Genetic Algorithm based Selective ENsemble
GCSA	Genetic-Based Crow Search Algorithm
GLCM	Gray-Level Co-Occurrence Matrix
GLRLM	Gray-Level Run-Length Matrix
GLSZM	Gray-Level Size Zone Matrix
GMM	Gaussian Mixture Models
GNB	Gaussian Naïve Bayes
GWO	Grey Wolf Optimization
HER	Electronics Health Records
HMM	Hidden Markov Model
HRV	Heart Rate Variability
iForest	isolation forest
IG	Information Gain
IMBO	Improved Monarch Butterfly optimization

Isomap	Isometric Mapping
KNN	K-Nearest Neighbours
LDL	low density lipoprotein
LFC	Loss Function Change
LM	Linear Method
LR	Logistic Regression
MAE	Mean Absolute Error
MBAR	ModifiedBoostARoota
MBO	Monarch Butterfly Optimization
MCI	Mild Cognitive Impairment
MDF	Modified Dragonfly algorithm
MI	Mutual Information
MIDDM	Multiple Infectious Disease Diagnostic Model
ML	Machine Learning
MMSE	Mini-mental state examination
MRIs	Magnetic Resonance Images
mRMR	MinimumRedundancy Maximum Relevance
MSE	Mean Squared Error
MSEN	Multistage Ensemble model
MVE	Majority Vote Ensemble
NGTDM	Neighborhood Gray-Tone Difference Matrix
NHANES III	Third National Health and Nutrition Examination Survey
OANN	Optimized Artificial Neural Network
OBL	Opposition-Based learning
OHE	One-Hot Encoding
OSLEM	Optimized Super Learner Ensemble Model
PCA	Principal Component Analysis
Pd	Parkinson's disease
PF-BAT	Parameter Free BAT

PF-FKNN	Parameter Free BAT Optimized Fuzzy K-nearest neighbour
Pre-MCI	Pre-Mild Cognitive Impairment
PSO	Particle Swarm Optimization
PVC	Prediction Values Change
PyPI	Python package Index
RF	Random Forest
RFE	Recursive Feature Elimination
RFF	ReliefF
RFS	Recursive Feature Selection
RMA	Replacing of Missing Attributes
SA	South African
SGD	Stochastic Gradient Descent
SLEM	Super-Learner Ensemble Model
SMA	Slime Mould Algorithm
SMO	Sequential Minimal Optimization
SMOTE	Synthetic Minority Over-Sampling Technique
SPM	Position-Specific Mutation
SSL	Semi-Supervised Learning
SVM	Support Vector Machines
SVR	Support Vector Regression
UFS	Univariate Feature Selection
VAE	variational Autoencoders
WOA	Whale Optimization algorithm
XGB	Xtreme gradient boosting
XGBC	XGBoost Classifier
XV	Xvariance

LIST OF SYMBOL

$\hat{y}_i^{(t)}$	prediction at t^{th} round
f_i	structure of a decision tree
x	independent variable
$f(x)$	dependent variable
S	set of examples
$pi(S)$	probability of an instance belonging to class i
\vec{X}	position vector
\vec{X}^*	best solution obtained
t	current iteration
$ \cdot $	the absolute value operation
\bullet	element-by-element multiplication
\vec{A} and \vec{C}	Two parameter
\vec{r}	random number in the interval $[0,1]$
\vec{a}	decreased linearly from 2 to 0 throughout the iterations
\vec{D}'	distance between the i^{th} whale
l	random number in $[-1,1]$
b	constant
p	random number of $[0,1]$.
$ A $	Random variable
\vec{X}_{rand}	random position vector
$F(i)$	fitness function
ϑ	whale population
<i>accuracy</i> (X)	classification accuracy of selected base classifier
Y	total number of base classifiers
γ	weighting parameter
n	Number of base classifiers
t	Percent of samples that are selected for constructing each base classifier

<i>g</i>	Percent of variables that are selected for constructing each base classifier
<i>ntg</i>	Number of whales constructed with base classifiers using Threshold as a parameter
<i>WOA_whales</i>	input <i>ntg</i> to WOA and return the best result whales for different sets
<i>Best_whales</i>	Select the top <i>ntg</i> whales from the <i>WOA_whales</i> with maximum diversity