HUNGER BEHAVIOUR CLASSIFICATION OF LATES CALCARIFER USING MACHINE LEARNING FOR AUTOMATIC DEMAND FEEDER THROUGH IMAGE PROCESSING

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DOCTOR OF PHILOSOPHY

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SUPERVISOR'S DECLARATION

I hereby declare that I have checked this thesis and in my opinion, this thesis is adequate in terms of scope and quality for the award of the degree of Doctor of Philosophy.

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STUDENT'S DECLARATION

I hereby declare that the work in this thesis is based on my original work except for quotations and citations which have been duly acknowledged. I also declare that it has not been previously or concurrently submitted for any other degree at Universiti Malaysia Pahang or any other institutions.

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Dottore del buco del culo

Vaffanculo! Vaffanculo!

ABSTRAK

Pemahaman dan pengecaman kelakuan ikan ketika lapar merupakan kunci dalam peningkatan produk akuakultur. Oleh itu, tesis ini mensasarkan kepada pengelasan ikan siakap (*Lates Calcarifer*) ketika lapar menggunakan teknik integrasi pemprosesan imej dan pembelajaran mesin. Teknik kluster min-k digunakan untuk menentukan jumlah kelas yang relevan daripada data mentah. Hasil teknik kluster min-k ini, dua kelas, “Lapar” dan “kenyang”, telah ditentukan sebagai relevan untuk penyelidikan ini berdasarkan ciri-ciri tertentu yang ditunjukan ketika ikan-ikan tersebut lapar dan kenyang. Ciri-ciri tersebut dianalisis melalui analisis plot kotak, dan Analisis Komponen Utama (PCA). Ciri yang telah dipastikan adalah COG x, COG y, dan penjumlahan pergerakan piksel. Pelbagai model pembelajaran mesin seperti Analisis Diskriminan (DA), Mesin Vektor Sokongan (SVM), *k*-Jiran Terdekat (*k*-NN) telah digunakan untuk menentukan model terbaik untuk membuat pengelasan keadaan ikan tersebut. Teknik SVM mampu memberikan pengelasan terbaik sehingga 99.00%. Penyelidik percaya teknik ini sesuai untuk digunakan dalam bidang penternakan ikan. Analisis tambahan dilakukan untuk memahami ritma sirkadian ikan dengan menilai ciri masa-bersiri. Pelbagai saiz tetingkap daripada 0.5 minit, 1.0 minit, 1.5 minit and 2.0 minit telah diselidiki bersama min, maksimum, minimum dan varian untuk setiap tempoh masa tersebut. PCA dan PCA pusingan varimax telah digunakan untuk menentukan ciri terbaik untuk pengelasan melalui SVM dan *k*-NN. Hasil analisis ini mendapati min dan varian untuk kesemua tempoh masa adalah ciri yang signifikan. Model pembelajaran mesin seperti DA, SVM, *k*-NN, Pokok Keputusan (Tree), Regresi Logistik (LR), Pokok Hutan Rawak (RF), Rangkaian Neural (NN), dinilai untuk mencari model yang terbaik dalam proses pengelasan ikan melalui ciri min dan varian. Penyelidik mendapati *k*-NN mempunyai prestasi terbaik dalam pengelasan tersebut dengan kejituan 96.47%. Untuk memperhalusi ketepatan model *k*-NN ini, hiperparameter telah dioptimumkan melalui Pengoptimuman Bayesian. Hasil pengoptimuman ini, penyelidik mendapati hiperparameter terbaik adalah Jarak Standard Euclidean dengan nilai k = 1 yang memberikan 97.16% kejituan pengelasan.

ABSTRACT

The understanding and identification of fish hunger behaviour are non-trivial in the aquaculture industry. This thesis aims at classifying the hunger state of *Lates Calcarifer* via the integration of computer vision and machine learning. Prior to the classification of the hunger states, the hunger state of the fish is identified through the *k*-means clustering technique and it was established that the hunger state could be demarcated into either 'Hungry' or 'Satiated'. Upon the identification of the hunger state, significant features that could contribute towards the accurate classification of the states are investigated. The aforesaid features are analysed by the box plot analysis and the Principal Component Analysis (PCA). The established features are COG x, COG y and the moving summation of the pixel. Different machine learning models were investigated by incorporating the identified features, i.e., Discriminant Analysis (DA), Support Vector Machine (SVM) and *k*-Nearest Neighbours (*k*-NN) and it was demonstrated that the SVM trained model is able to classify up to 99.00%, suggesting that the developed system is viable for fish farming. A supplementary analysis was further carried out to understand the circadian rhythm of the fish by evaluating the time-series features. Different window sizes ranging from 0.5 min, 1.0 min, 1.5 min and 2.0 min coupled with the mean, maximum, minimum and variance for each of the distinctive temporal window sizes are investigated. PCA and PCA varimax rotation was employed in order to identify the best features through classifying it via SVM and *k*-NN. It was shown that the mean and variance of all temporal sizes are significant. In addition, the efficacy of different models based on the identified secondary features, namely DA, SVM, *k*-NN, Decision Tree (Tree), Logistic Regression (LR), Random Forest Tree (RF) and Neural Network (NN) are evaluated. It was found that the *k*-NN yielded the highest classification accuracy with 96.47% from the test sets. In order to further refine the *k*-NN model developed, hyperparameter optimization by means of Bayesian Optimization was carried out. Through the optimization process, the best hyperparameters that could attain a classification accuracy of 97.16% are the Standardized Euclidean distance metric with a *k* value of one.

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LIST OF SYMBOLS

c	Summation of distance
d	Euclidean distance
i	Sequence number
j	Sequence number
k	Number of neighbors
l	Sequence number
$u(t)$	Time series first warped signal
$v(t)$	Time series second warped signal
x	Points of cluster
y	Points of cluster
z	Input parameter of sigmoid
C	Total distance
C_i	Mean
D	Warping path distance
N	Total number of data points
R	Repeatability score
U	Time series first signal
V	Time series second signal
ξ	Warping path
ρ	Euclidean distance
ξ_i	Loss term
µ	Mean
$\mathbb{R}$	Set of real number
ϕ	Sigmoid function
Θ	Radian

LIST OF ABBREVIATIONS

3D	Three Dimensional
AI	Artificial Intelligence
ANN	Artificial Neural Network
BCT	Black Chinned Tilapia
CART	Classification and Regression Tree
CCD	Charge Coupled Device
COG	Centre of Gravity
CV	Cross Validation
DA	Discriminant Analysis
DTW	Dynamic Time Warping
EMG	Electromyography
F_1	F_1 Score
FP	False Positive
FN	False Negative
IR	Infrared
k-NN	*K*-Nearest Neighbors
LR	Logistic Regression
ML	Machine Learning
MSE	Mean Squared Error
NaN	Not-a-Number
NT	Nile Tilapia
OFT	Open Field Test
PCA	Principal Component Analysis
RF	Random Forest Tree
SGR	Specific Growth Rate
SMA	Simple Moving Average
SMO	Sequential Minimal Optimization
SMBO	Sequential Model Based Optimization
SVM	Support Vector Machine
TP	True Positive
TN	True Negative

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