**Gait Pattern Recognition through Platform based on XGBoost Mo

Hawks Optimization

Lie Yu, Pengzhi Mei, and Lei Ding

Abstract-This study developed a gait pattern classification

system based on ground contact forces meas Sait Pattern Recognition through F**
Platform based on XGBoost Mode
Hawks Optimization
Lie Yu, Pengzhi Mei, and Lei Ding
Abstract—This study developed a gait pattern classification
system based on ground contact forces mea **sensors embedded inside the shoe sole. The data transmission is frame-level part feature extractor in combination Visual Conduct of pressure can be used to extract the motion features**
extract the motion capture module to extract motion features
extract the motion features and decompo In through Force Sensor

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frame-level part feature extractor in combination with a

micro-motion capture module to extract motion features

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Lie Yu, Pengzhi Mei, and Lei Ding

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Gait Pattern Recognition through Force Sensor

Platform based on XGBoost Model and Harris'

Hawks Optimization

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Gait Pattern Recognition through Force Sensor

Platform based on XGBoost Model and Harris'

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Recognition through Force Sensor

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**Faction based on XGBoost Mode

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 Abstract—This study developed a gait pattern classification

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facilitate **Platform based on XGBoost Mome

Hawks Optimizatio**

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 Abstract—This study developed a gait pattern classification

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system bas **algorithm is used to identify the gait patterns, and the basic idea** of XGBoost is to use second-order derivatives to make the allocations there are allocations from the second-order order allocation of the properties of XGBoost is to use second-order derivatives to make the approach **locate in the more interesting, and enable block storage for parallel and the effectively incorporated into the function more precise more precise in the motion frame-level part feature extystem based on ground contact fo** Lie Yu, Pengzhi Mei, and Lei Ding
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 prevent tree sensors embedded inside the shoe sole. The data transmission is

facilitated via the Bluetooth Lie Yu, Pengzhi Mei, and Lei Ding
system based on ground contact forces measured by six force
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sensors embedded inside the shoe sole. The d *Abstract***—This study developed a gait pattern classification** frame-level part feature eystem based on ground contact forces measured by six force micro-motion capture modes ensors embedded inside the shoe sole. The data Abstract—This study developed a gait pattern classification frame-level part
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sensors embedded inside the shoe sole. The data transmission is faci Abstract—This study developed a gait pattern classification
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fracilitated via the should inside the should integrated into an STM32 extract the motion feat

facilitated via the Bluetooth module integrated into an STM32 ext sensors embedded inside the shoe sole. The data transmission is

microcontroller. The extreme gradient boosting (XGBoost)

algorithm is used to identify the gait patterns, and the basic

idea of XGBoost is to use second-or **facilitated via the Bluetooth module integrated into an STM32**
 **activident in its used to identify the gait patterns, and the basic

algorithm is used to identify the gait patterns, and the basic

loss function more prec** microcontroller. The extreme gradient boosting (XGBoost)

ilegation is used to identify the gait patterns, and the basic

idensity to use scoond-order derivatives to make the

loss function more precise, incorporate regula algorithm is used to identify the gait patterns, and the basic
diga of XGBoost is to use second-order derivatives to make the
approaches involve complementation for the actival prevent rece overfitting, and enable block st idea of XGBoost is to use second-order delays function more precise, incorporat
prevent tree overfitting, and enable block
computation. By optimizing the XGBoost
algorithms, the exploration capabilities of
effectively inco **INTEONIGTION**
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algorithms, the exploration capabilities of these algorithms are
effectively incorporated into the fusion model. Experimental
results indicate that the XGBoost alg ed into the fusion model. Experimental

the XGBoost algrithm optimized by

inization (HHO) outperforms the other

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nms. Specifically, the HHO-XGBoost

of 97.41%, 97.03%, and 97.22% severally

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achieved high values of 97.41%, 97.03%, and 97.22% severally
in the metrics of precision, recall, and F1 score. This research
in the metrics of precision, recal Extraction and the metrics of precision, recall, and F1 sore. This research reaction force (GRF) is
illustrates the HHO-XGBoost method's superiority in gait increasingly common. Be
phase recognition.
Index Terms—Gait pat Example the matrices of the term is the term in the term is the example of the second in the second in the second of the second in the se **Example 19 and 19 Example 18 Consumption** and the searchers to end het the resultion of the search the searcher than the searcher than the searcher of the searcher of the searcher of the Fast From the Fast From the Fast From the Fast From Index Terms—Gait pattern classification, Ground contact mean, variance, and kurt
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Learning the movement state du Eastimes through the Fast Fouring the Tast Fouring and the Fast Fouring that and the Fast Fouring the movement state during human walking. It has been extensively utilized in diverse fields such as [16-17]. As support vect I. INTRODUCTION

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It has been extensively utilized in diverse fields **C** ait phase recognition is a widely adopted technique for

It has been extensively utilized in diverse fields such as

[16-17]. As support vector medicine [1-2], forensic detection [3-4], small furniture boosting are wid **Lassessing the movement state during human walking.** learning, numerous classificatient It has been extensively utilized in diverse fields such as [16-17]. As support vector mandicine [1-2], forensic detection [3-4], sma It has been extensively utilized in diverse fields such as [16-17]. As support vector medicine [1-2], forensic detection [3-4], smart furniture boosting are widely used in control [5-6], and robot exoskeleton control [7]. medicine [1-2], forensic detection [3-4], smart furniture boosting are widely used for the gait data could enable the researches to conduct more in recent years, the XGBoost comprehensive assessments of human movement and ore effective response strategies. For individuals without science comperouslysical impairments, during the same movement pattern, exceptional perticle conduction and the state of the state of the state of the state of the in the same movement pattern, exceptional performance

ch leg exhibits similar motion, with only a phase lag depends on the hyperpara

tween different limbs [8]. However, analyzing the gait left at their default setting

t Processor at the School of Electronic and corresonning and the motion pattern corresonning and the state. Corresonning the same those with limb identify the optimal impairments. There are various methods for determining th cach reg exinons similar motion, whir only a ph
between different limbs [8]. However, analyzing d
data becomes crucial for controlling the exoskele
people who use the robotic exoskeletons or those w:
impairments. There are Extract the sixteen of the stocial for controlling the stockeleton for achieved. Selecting a scople who use the robotic exoskeletons or those with limb identify the optimal hypairments. There are various methods for determ data becomes crucial for controlling the exoskeleton for achieved. Selecting a
people who use the robotic exoskeletons or those with limb identify the optimal
impairments. There are various methods for determining the chha people who use the robotic exoskeletons or those with limb identify the optimal
impairments. There are various methods for determining the chancing the XGB
movement state. For example, researchers can utilize integrated wi Gait phase recognition is a widely adopted technique for
It has been extensively utilized in diverse fields such as [16-17]. As support vector machines (SVM) and gradient

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lyu@wtu.edu.cn)
Pengzhi Mei is a postgraduate student at the School of Electronic and Manuscript received May 15, 2024; revised N
This work was supported by the National Na
China "Research on motion pattern recognitior
on curve similarity model" (NO.62106178).
Lie Yu is an Associate Professor at the
Electr

1006242095@qq.com)
Lei Ding is an Associate Professor at the School of Computer Science

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Frame-level part feature extractor in combination with a

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10]. A two-dimensional center of pressure can be used to
tract the motion features and decompose the planar
igectories for accurate localization [11]. However, these
pr [9-10]. A two-dimensional center of pressure can be used to extract the motion features and decompose the planar trajectories for accurate localization [11]. However, these approaches involve complex force processing or re extract the motion features and decompose the planar
trajectories for accurate localization [11]. However, these
approaches involve complex force processing or require
handling intricate signals. Consequently, wearable sen trajectories for accurate localization [11]. However, these
approaches involve complex force processing or require
handling intricate signals. Consequently, wearable sensors
offer a cost-effective and easily installable so

approaches involve complex force processing or require handling intricate signals. Consequently, wearable sensors offer a cost-effective and easily installable solution for gait phase recognition [12-13]. This study introd handling intricate signals. Consequently, wearable sensors
offer a cost-effective and easily installable solution for gait
phase recognition [12-13]. This study introduces an
intelligent shoe sole equipped with six force-s offer a cost-effective and easily installable solution for gait
phase recognition [12-13]. This study introduces an
intelligent shoe sole equipped with six force-sensitive
resistors (FSRs) to collect data. By processing an phase recognition [12-13]. This study introduces an intelligent shoe sole equipped with six force-sensitive resistors (FSRs) to collect data. By processing and labeling the data from the wearable sensors, the movement stat intelligent shoe sole equipped with six force-sensitive
resistors (FSRs) to collect data. By processing and labeling
the data from the wearable sensors, the movement state was
effectively determined.
Using insole pressure resistors (FSRs) to collect data. By processing and labeling
the data from the wearable sensors, the movement state was
effectively determined.
Using insole pressure sensors to collect the ground
reaction force (GRF) gait e data from the wearable sensors, the movement state was
fectively determined.
Using insole pressure sensors to collect the ground
action force (GRF) gait data features has become
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Using insole pressure sensors to collect the ground

reaction force (GRF) gait data features has become

increasingly common. Before classifying data by machine

learning algorithms, selecting appr Using insole pressure sensors to collect the ground
reaction force (GRF) gait data features has become
increasingly common. Before classifying data by machine
learning algorithms, selecting appropriate features is
essentia reaction force (GRF) gait data features has become
increasingly common. Before classifying data by machine
learning algorithms, selecting appropriate features is
essential. In gait data analysis, time domain features such increasingly common. Before classifying data by
learning algorithms, selecting appropriate fe
essential. In gait data analysis, time domain feature
mean, variance, and kurtosis are often conside
These are further transform arming algorithms, selecting appropriate features is
sential. In gait data analysis, time domain features such as
ean, variance, and kurtosis are often considered [14].
nese are further transformed into frequency domain
tu essential. In gait data analysis, time domain features such as
mean, variance, and kurtosis are often considered [14].
These are further transformed into frequency domain
features through the Fast Fourier Transform [15]. C

mean, variance, and kurtosis are often considered [14].
These are further transformed into frequency domain
features through the Fast Fourier Transform [15]. Collected
data undergoes weighting and normalization processes
b These are further transformed into frequency domain
features through the Fast Fourier Transform [15]. Collected
data undergoes weighting and normalization processes
before classification by machine learning models.
With ad features through the Fast Fourier Transform [15]. Collected
data undergoes weighting and normalization processes
before classification by machine learning models.
With advances in artificial intelligence and machine
learni data undergoes weighting and normalization processes
before classification by machine learning models.
With advances in artificial intelligence and machine
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With advances in artificial intelligence and machine
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boosting are widely used for training and learning from
 learning, numerous classification algorithms have emerged
[16-17]. As support vector machines (SVM) and gradient
boosting are widely used for training and learning from
labeled data [18-19].
In recent years, the XGBoost al [16-17]. As support vector machines (SVM) and gradient
boosting are widely used for training and learning from
labeled data [18-19].
In recent years, the XGBoost algorithm has been widely
used as a robust classifier, and w boosting are widely used for training and learning from
labeled data [18-19].
In recent years, the XGBoost algorithm has been widely
used as a robust classifier, and widely applied in data
science competitions and industri labeled data [18-19].

In recent years, the XGBoost algorithm has been widely

used as a robust classifier, and widely applied in data

science competitions and industrial settings due to its

exceptional performance [20-2 In recent years, the XGBoost algorithm has been widely
used as a robust classifier, and widely applied in data
science competitions and industrial settings due to its
exceptional performance [20-22]. Its optimization is la used as a robust classifier, and widely applied in data
science competitions and industrial settings due to its
exceptional performance [20-22]. Its optimization is largely
depends on the hyperparameters. When these parame ience competitions and industrial settings due to its
ceptional performance [20-22]. Its optimization is largely
pends on the hyperparameters. When these parameters are
 $\hat{\bf{a}}$ at their default settings, optimal performa exceptional performance [20-22]. Its optimization is largely
depends on the hyperparameters. When these parameters are
left at their default settings, optimal performance is often not
achieved. Selecting a suitable optimiz depends on the hyperparameters. When these parameters are left at their default settings, optimal performance is often not achieved. Selecting a suitable optimization algorithm to identify the optimal hyperparameters is th left at their default settings, optimal performance is often not
achieved. Selecting a suitable optimization algorithm to
identify the optimal hyperparameters is thus critical for
enhancing the XGBoost's classification acc

meant state. For example, researchers can utilize integrated with XGBoos
ovement state. For example, researchers can utilize integrated with XGBoos
mputer vision to assess movement or employ a genetic algorithms (G
algorit movement state. For example, researchers can utilize integrated with XGE
computer vision to assess movement or employ a genetic algorithms
algorithm (AOA) [24
This work was supported by the National Natural Science Foundat Manuscript received May 15, 2024; revised November 22, 2024.

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rune similarly model (NO.62106178).

Case Computer School of Electronic and

curve simila Manuscript received May 15, 2024; revised November 22, 2024.

This work was supported by the National Natural Science Foundation of

China "Research on motion pattern recognition of exoskeleton robot based

Lie Yu is an As achieved. Selecting a suitable optimization algorithm to
identify the optimal hyperparameters is thus critical for
enhancing the XGBoost's classification accuracy. When
integrated with XGBoost, optimization techniques such identify the optimal hyperparameters is thus critical for
enhancing the XGBoost's classification accuracy. When
integrated with XGBoost, optimization techniques such as
genetic algorithms (GA) [23], arithmetic optimization enhancing the XGBoost's classification accuracy. When
integrated with XGBoost, optimization techniques such as
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algorithm (AOA) [24], coati optimization algorithm (COA)
 integrated with XGBoost, optimization techniques such as
genetic algorithms (GA) [23], arithmetic optimization
algorithm (AOA) [24], coati optimization algorithm (COA)
[25], and Harris hawks optimization (HHO) [26-29] can
 genetic algorithms (GA) [23], arithmetic optimization
algorithm (AOA) [24], coati optimization algorithm (COA)
[25], and Harris hawks optimization (HHO) [26-29] can
effectively identify the optimal hyperparameters.
This st

Example the sensitivity are loaded at different points of the shoe soletion. This study developed a smart intelligent shoe integrated with six FSRs. (b) The STM32 Figure 3(a) displays the force information and the Blueto The force data from the FSRs are collected via an STM32

Expective digitized. Then the data were collected. The

Fig. 1. (a) The intelligent shoe integrated with six FSRs. (b) The STM32

Figure 3(b) shows the fall

Figure Data Acquisition Board

Fig. 1. (a) The intelligent shoe integrated with six FSRs. (b) The STM32

Figure 3(a) displays the force v

Figure 3(a) shows the labeled

collects the force information and the Bluetooth module tr Data Acquisition Board

Fig. 1. (a) The intelligent shoe integrated with six FSRs. (b) The STM32

Figure 3(a) displays the formation into the host.

It is evident information and the Bluetooth module transmits the ground, Data Acquisition Board

Fig. 1. (a) The intelligent shoe integrated with six FSRs. (b) The STM32

Figure 3(a) displays the force

Figure 3(a) shows the labeled

collects the force information and the Bluetooth module tran Experiments, each FSR was calibrated by applying various
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Information into the bost.

concerns information into the bost.

This study developed a smart intelligent shoe integ Fig. 1. (a) The intelligent shoe integrated with six FSRs. (b) The STM32 pressure values. It is evident
collects the force information and the Bluetooth module transmits the
information into the host.
find information int collects the force information and the Bluetooth module transmits the ground, the values of the and FSR3) increase rap

This study developed a smart intelligent shoe integrated When the FSRs under the with six FSRs to moni information into the host.

This study developed a smart intelligent shoe integrated

With six FSRs to monitor the GRFs. As depicted in Figure 1,

the FSRs with strong adhesion, bend resistance, and high

sensitivity are p

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 1989
 1989 Bluetooth module via a serial port and then series of operations is performed offline.

Bluetooth module via a serial port and then sent to the host computer. The computer of this system is allustrated in Figure 2. The 12-Fig. 3. Gait Phase Fig. 3. Gait data are divided into specific from six FSRs. (b) The labeling of gait principle and the experimental procedure
Fig. 3. The working principle and the experimental procedure
IIII SH The compu Fig. 3. Gait Ada are divided in

Fig. 2. The working principle and the experimental procedure

The primary operating principle of this system is

illustrated in Figure 2. The 12-bit analog-to-digital converter

(ADC) integ

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B. Experimental protocol
Ten participants (six males and four females, with a n
height of 160 \pm 5.9 cm and a mean age of 22 \pm 3.3 ye
who were free from foot-related conditions volunteere **of Applied Mathematics**
Experimental protocol
Ten participants (six males and four females, with a mean
ight of 160 ± 5.9 cm and a mean age of 22 ± 3.3 years)
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 B. Experimental protocol

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height of 160 ± 5.9 cm and a mean age of 22 ± 3.3 years)

who were free from foot-related conditions **Shock Continuously and Summann Continuously and Summann Separation**
 Shock continuously at a constant speed of 3 km/h on were free from foot-related conditions volunteered for this study. The participants were instruct **al of Applied Mathematics**
 B. Experimental protocol

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Ten participants (six males and four females, with a mean

height of 160 \pm 5.9 cm and a mean age of 22 \pm 3.3 years)

who were free from foot-related conditions volunteered for

this study. B. *Experimental protocol*
Ten participants (six males and four femal
height of 160 ± 5.9 cm and a mean age of 2
who were free from foot-related conditions
this study. The participants were instructed t
shoe and walk co Ten participants (six males and four females,
height of 160 ± 5.9 cm and a mean age of 22
who were free from foot-related conditions vol
this study. The participants were instructed to d
shoe and walk continuously at a ight of 160 ± 5.9 cm and a mean age of 22 ± 3.3 years)
no were free from foot-related conditions volunteered for
s study. The participants were instructed to don the smart
oe and walk continuously at a constant speed who were free from foot-related conditions volunteered for
this study. The participants were instructed to don the smart
shoe and walk continuously at a constant speed of 3 km/h on
a treadmill for a duration of 2 minutes. me were normalized and walk continuously at a constant speed of 3 km/h on
a treadmill for a duration of 2 minutes. Before data
collection, participants were instructed to don the smart
shoe and walk continuously at a cons

Examples are the FSRs with strong adhesion, bend resistance, and high band the strong data with six FSRs. (b) The STM32 generate a schematic of plant Figure 3(a) displays the force Figure 3(a) displays the force Figure 3(a and walk continuously at a constant speed of 3 km/h on
shoe and walk continuously at a constant speed of 3 km/h on
a treadmil for a duration of 2 minutes. Before data
collection, participants were instructed to adjust the Since and wank columinously at a constant speed of 3 KIDT on
a treadmill for a duration of 2 minutes. Before data
collection, participants were instructed to adjust the insole
position. Ensuring correct placement helps mai a treadmin for a duration of 2 influences. Before data
collection, participants were instructed to adjust the insole
position. Ensuring correct placement helps maintain optimal
sensor contact, thereby minimizing testing er collection, participants were instructed to adjust the insole
position. Ensuring correct placement helps maintain optimal
sensor contact, thereby minimizing testing errors caused by
insole movement.
C. Data analysis
During position. Ensuring correct placement helps maintain optimal
sensor contact, thereby minimizing testing errors caused by
insole movement.
C. Data analysis
During the experiment, several sets of plantar pressure
data were co sensor contact, thereby minimizing testing errors caused by

insole movement.

C. Data analysis

During the experiment, several sets of plantar pressure

data were collected. The collected voltage signals were

digitized. Insole movement.

C. Data analysis

During the experiment, several sets of plantar pressure

data were collected. The collected voltage signals were

digitized. Then the data were normalized and integrated to

generate a s C. Data analysis

During the experiment, several sets of plantar pressure

data were collected. The collected voltage signals were

digitized. Then the data were normalized and integrated to

generate a schematic of planta C. Data analysis

During the experiment, several sets of plantar pressure

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digitized. Then the data were normalized and integ During the experiment, several sets or plantar pressure
data were collected. The collected voltage signals were
digitized. Then the data were normalized and integrated to
digitare a schematic of plantar pressure during mov

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D. Reference gait labels
In a typical walking cycle, foot movement is continue
and cyclic. It can be divided into four distinct phases: h
down (HD), standing horizontal (SH), toe tip (TT), a IAENG International Journal of Applied Mathemation
 Reference gait labels into the trained model

In a typical walking cycle, foot movement is continuous accuracy of the model v

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D. Reference gait labels

In a typical walking cycle, foot movement is continuous

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D. Reference gait labels

in a typical walking cycle, foot movement is continuous

and cyclic. It can be divided into four distinct phases: heel

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D. Reference gait labels

In a typical walking cycle, foot movement is continuous

and cyclic. It can be divided into four distinct phases: heel

down (HD), standing hori **IAENG International Journal of Applied Mathematics**
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In a typical walking cycle, foot movement is continuous accuracy of the model to pred

and cyclic. It can be divided into four distinct phas **IAENG International Journal of Applied Mathematics**

D. Reference gait labels

into the trained model to preced in a typical walking cycle, foot movement is continuous accuracy of the model was determined and cyclic. It **IAENG International Journal of Applied Mathematics**

D. Reference gait labels

In a typical walking cycle, foot movement is continuous

into the trained model to precent in the trained model of the model was deter

and cy **IAENG International Journal of Applied Mathematic**
 D. Reference gait labels into the trained model to provide the and cyclic. It can be divided into four distinct phases: heel patterns and the actual labele down (HD), *Reference gait labels*
 D. Reference gait labels

In a typical walking cycle, foot movement is continuous

and cyclic. It can be divided into four distinct phases: hell

down (HD), standing horizontal (SH), toe tip (TT) D. Reference gait labels

In a typical walking cycle, foot movement is continuous

and cyclic. It can be divided into four distinct phases: hell

and cyclic. It can be divided into four distinct phases: hell

are are part D. Reference gait labels

into the trained model

and cyclic. It can be divided into four distinct phases: heel

and cyclic. It can be divided into four distinct phases: heel

down (HD), standing horizontal (SH), toe tip (*D. Reference gait labels*
In a typical walking cycle, foot movemen
and cyclic. It can be divided into four distin
down (HD), standing horizontal (SH), toe
swing (SW). Figure 3 illustrates the labeling
corresponding to pre In a typical walking cycle, foot movement is continuous

accuracy of the model was det

d cyclic. It can be divided into four distinct phases: heel

win (HD), standing horizontal (SH), toe tip (TT), and

ing (SW). Figure 3 and cyclic. It can be divided into four distinct phases: heel
down (HD), standing horizontal (SH), toe tip (TT), and
accuracy, we use the HHO a
swing (SW). Figure 3 illustrates the labeling of gait patterns are are the HHO down (HD), standing horizontal (SH), toe tip (TT), and

swing (SW). Figure 3 illustrates the labeling of gait patterns

corresponding to pressure data during three cycles. Figure 4 algorithm to optimize the 2

shows the di swing (SW). Figure 3 illustrates the labeling of gait patterns
corresponding to pressure data during three cycles. Figure 4 algorithm to optimize the
shows the division of gait phases based on the data from classification

corresponding to pressure data during three cycles. Figure 4 algorithm to optimize the
shows the division of gait phases based on the data from
classification is depicted in Fi
various FSRs, which are categorized as either shows the division of gait phases based on the data from
various FSRs, which are categorized as either on-ground or
off-ground statuses. In these figures, the white dot
represents the off-ground status. When the black ded various FSRs, which are categorized as either on-ground or
off-ground statuses. In these figures, the white dot
represents the off-ground status. The differentiation between on-ground status is define in and
and off-ground represents the off-ground status, while the black dot denotes
the on-ground status. The differentiation between on-ground
and off-ground statuses is determined by setting a threshold
for the GRFs.
When the hele touches the For the GRFs.

When the heel touches the ground, it is definestate, in which only FSR1, FSR2, and FSR3 re

When all six FSRs detect force, the label valu

maximum. We define this as the SH state, which

longest-lasting pha When the heel touches the ground, it is defined as the HD
the, in which only FSR1, FSR2, and FSR3 register force.

hen all six FSRs detect force, the label value reaches its

ximum. We define this as the SH state, which is

From an six 1 six curve of the dispared by the dispared of the miximum. We define this as the SH state, which is also the
dingest-lasting phase in the movement cycle. Only the three
forefoot FSRs (FSR4, FSR5, and FSR6) re between different gait patterns. It can accelerate model
convergences and interpretations are on the significant
state. When stepping forward with the foot in the air, all
FSR values drop to zero. This state is defined as conception and enhance both accuracy and stability. By

forcefor FSRs (FSRA, FSRS, and FSR6) register force when

state. When stepping forward with the foot in the air, all

FSR values drop to zero. This state is defined a Standard Core is the data when the took We define it as the Toe Touch (TT)

state. When stepping forward with the foot in the air, all

state. When stepping forward with the foot in the air, all

FSR values drop to zero. T standard on the toes. We define it as the 10e 10uch (11)

state. When stepping forward with the foot in the air, all

FSR values drop to zero. This state is defined as the SW.

E. Data preprocessing

One to the significan state. When stepping forward with the foot in the air, all

FSR values drop to zero. This state is defined as the SW.

E. Data preprocessing

One to the significant variations in gait patterns

orresponding to the GRFs co FSR values drop to zero. This state is defined as
 E. Data preprocessing

Due to the significant variations in ga

corresponding to the GRFs collected by se

preprocessing is typically required. Normaliz

essential step preprocessing is typically required. Normalization is an

between different gait patterns. It can accelerate model

between different and enhance both accuracy and stability. By

standardizing the data, biases between ga essential step that helps to mitigate dimensional disparities
between different gait patterns. It can accelerate model
convergence and enhance both accuracy and stability. By
standardizing the data can also make it more
c

$$
x_{norm} = \frac{x - \mu}{\sigma}
$$
 (1) decision tree fra
XGBoost is its s

between different gait patterns. It can accelerate model
convergence and enhance both accuracy and stability. By
standardizing the data, biases between gait patterns can be
reduced. Standardizing the data can also make it convergence and enhance both accuracy and stability. By

standardizing the data, biases between gait patterns can be

reduced. Standardizing the data can also make it more

comparable and interpretable. The normalization standardizing the data, biases between gait patterns can be

reduced. Standardizing the data can also make it more

comparable and interpretable. The normalization equation is
 $x_{norm} = \frac{x - \mu}{\sigma}$ (1) x_{r} accision tree f reduced. Standardizing the data can also make it more

comparable and interpretable. The normalization equation is A. Basic Principle of XGBoost

presented below.
 $x_{norm} = \frac{x - \mu}{\sigma}$ (1) GGBoost is an algori

implementatio comparable and interpretable. The normalization equation is
 $x_{norm} = \frac{x - \mu}{\sigma}$ (1) accision tree in SGBo implementation

where μ represents the average value, and σ represents the different regulat

standard deviat $x_{norm} = \frac{x - \mu}{\sigma}$ (1) decision
algorith
e average value, and σ represents the
tata normalization and standardization
essing techniques that improve the difference
bility of machine learning models.
consistency in data σ

ACODOS is algorithm provides effective

algorithm provides effective

and *o* represents the different regularization techniq

example the accuracy of machine learning models.

Formance and stability of machine lear where μ represents the average value, and σ represents the different regularization tech
standard deviation. Data normalization and standardization the way, the prediction ac
are common preprocessing techniques that where μ represents the average value, and σ represents the strandard deviation. Data normalization and standardization and standardization and standardization increasion technom perpocession increases the prediction

standard deviation. Data normalization and standardization

are common prepocessing techniques that improve the predictive

proved. The predictive

proved. The predictive

These methods ensure consistency in data normaliz are common preprocessing techniques that improve the argument and stability of machine learning models.
These methods ensure consistency in data normalization and
reduce the impact of feature variation. It also makes the
 performance and stability of machine learning models.

These methods ensure consistency in data normalization and

reduce the impact of feature variation. It also makes the

model process data more efficiently and accurat These methods ensure consistency in data normalization and

reduce the impact of feature variation. It also makes the

model process data more efficiently and accurately.

III. METHOD

To improve the accuracy of gait phas From the mpact of teature variation. It also makes the

del process data more efficiently and accurately.

To improve the accuracy of gait phase classification, this objective function of X

ddy employed the XGBoost algor model process data more efficiently and accurately.

The method of Marco prediction result, and f_k denote

study employed the XGBoost algorithm for gait phate objective function of XGBoost

dientification. The XGBoost a III. METHOD

To improve the accuracy of gait phase classification, this objective function of XGBoost is

study employed the XGBoost algorithm for gait pattern which are the loss function and identification. The XGBoost a III. METHOD where *m* represents the number

To improve the accuracy of gait phase classification, this

study employed the XGBoost algorithm for gait pattern

identification. The XGBoost algorithm is an optimized objecti To improve the accuracy of gait phase classification, this prediction result, and f_k denots
study employed the XGBoost algorithm for gait pattern which are the loss function
identification. The XGBoost algorithm is an o

and Solution Mathematics
into the trained model to predict the gait patterns. The
accuracy of the model was determined by the predicted gait
patterns and the actual labeled data. To further enhance
accuracy, we use the H **and of Applied Mathematics**
into the trained model to predict the gait patterns. The
accuracy of the model was determined by the predicted gait
patterns and the actual labeled data. To further enhance
accuracy, we use the **and of Applied Mathematics**
into the trained model to predict the gait patterns. The
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into the trained model to predict the gait patterns. The
accuracy of the model was determined by the predicted gait
patterns and the actual labeled data. To further enhance
accuracy, we use the HH **and of Applied Mathematics**
into the trained model to predict the gait patterns. The
accuracy of the model was determined by the predicted gait
patterns and the actual labeled data. To further enhance
accuracy, we use the

decision tree framework. One of the main advantages of Best Parameters

Mentification layer

Recognition Rate

Fig. 5. Flow diagram of HHO optimizing XGBoost

A. Basic Principle of XGBoost

The XGBoost is an algorithm designed for practical

implementation, which is based on t and the main of the main space of the main space of the main space of the main space of the same of the solution of the solution of the solution of the main space of the main space of the main space of the main space of th Recognition Rate

The Recognition Rate

Tig. 5. Flow diagram of HHO optimizing XGBoost

A. Basic Principle of XGBoost

The XGBoost is an algorithm designed for practical

implementation, which is based on the gradient-boos Examples and the model is greatly
the prediction accuracy of the model in the XGBoost
The XGBoost is an algorithm designed for practical
implementation, which is based on the gradient-boosting
decision tree framework. One **Example 18**
 **Examplementation, which is based on the gradient-boosting

decision tree framework. One of the main advantag** Fig. 5. Flow diagram of HHO optimizing XGBoost
 A. Basic Principle of XGBoost

The XGBoost is an algorithm designed for p

implementation, which is based on the gradient-l

decision tree framework. One of the main advan mplementation, which is based of the gradient-boosing
decision tree framework. One of the main advantages of
XGBoost is its support for linear classifiers. The XGBoost
algorithm provides effective solutions by introducing XGBoost is its support for linear classifiers. The XGBoost
algorithm provides effective solutions by introducing
different regularization techniques into the loss function. By
the way, the prediction accuracy of the model algorithm provides effective solutions by introducing
different regularization techniques into the loss function. By
the way, the prediction accuracy of the model is greatly
improved. The predictive model of XGBoost can b

$$
\hat{y}_i^m = \sum_{k=1}^m f_k(x_i) \tag{2}
$$

different regularization techniques into the loss function. By
the way, the prediction accuracy of the model is greatly
improved. The predictive model of XGBoost can be
formulated as follows:
 $\hat{y}_i^m = \sum_{k=1}^m f_k(x_i)$ (2) the way, the prediction accuracy of the model is greatly
improved. The predictive model of XGBoost can be
formulated as follows:
 $\hat{y}_i^m = \sum_{k=1}^m f_k(x_i)$ (2)
where *m* represents the number of decision trees, \hat{y} is where *m* represents the number of decision trees, \hat{y} is the prediction result, and *f_k* denotes the *k*-*th* decision tree. The objective function of XGBoost is divided into two parts, which are the loss function where *m* represents the number of decision trees, \hat{y} is the prediction result, and f_k denotes the *k*-th decision tree. The objective function of XGBoost is divided into two parts, which are the loss function and

$$
Obj = \sum_{i=1}^{n} l(y_i, \hat{y}_i^{m-1} + f_m(x_i)) + \Omega(f_m) + C
$$
 (3)

following.

$$
\Omega(f_m) = \gamma J + \frac{1}{2} \lambda \sum_{j=1}^{J} w_j^2
$$
\n(4) *Xrand* is a ran population with average position.

IAENG International Journal of Applied Mathematic
 $\Omega(f_m) = \gamma J + \frac{1}{2} \lambda \sum_{j=1}^{J} w_j^2$ (4) $\begin{array}{c} X_{rand} \text{ is a randomly selected} \\ \text{population within the current} \\ \text{average position of the current} \\ \text{are the upper and lower bounds} \\ \text{scores for different leaf nodes. Moreover, both } \gamma \text{ and } \lambda \text{ are} \\ \text{customization parameters. By combining Equations (3) and \\ \text{(4), the loss function can be expressed as:} \quad \text{J n} \\ \end{array}$ **IAENG International Journal of Applied M**
 $\Omega(f_m) = \gamma J + \frac{1}{2} \lambda \sum_{j=1}^{J} w_j^2$ (4) population within average position c
where *J* represents the number of leaf nodes, and ω is the *R*₃, and *R*₄ are rand
scores for **IAENG International Journal of Applied Mathematic
** $\Omega(f_m) = \gamma J + \frac{1}{2} \lambda \sum_{j=1}^{J} w_j^2$ **(4) population within the current

average position of the current

where** *J* **represents the number of leaf nodes, and** ω **is the R IAENG International Journal of Appli**
 $\Omega(f_m) = \gamma J + \frac{1}{2} \lambda \sum_{j=1}^{J} w_j^2$ (4) population v

where *J* represents the number of leaf nodes, and ω is the *R*₃, and *R*₄ are

scores for different leaf nodes. Moreove where *J* represents the number of leaf nodes, and ω is the R_3 , an scores for different leaf nodes. Moreover, both γ and λ are customization parameters. By combining Equations (3) and (4), the loss function ca

$$
Obj = \sum_{i=1}^{n} [l(y_i, \hat{y}_i^{m-1}) + g_i f_m(x_i) + \frac{1}{2} h_i f_m^2(x_i)] + \Omega(f_m) + C(5)
$$
 Calculate fitness

$$
g_i = \frac{\partial l(y_i, \hat{y}_i^{m-1})}{\partial \hat{y}_i^{m-1}}
$$
 (6)

$$
h_i = \frac{\partial^2 l(y_i, \hat{y}_i^{m-1})}{\partial (\hat{y}_i^{m-1})^2}
$$
 (7)

$$
w_j^* = -\frac{\sum g_i}{\sum h_i + \lambda} \tag{8}
$$

stituting Equations (4), (6), and (7) into Equation
\nlutions can be derived as follows:
\n
$$
w_j^* = -\frac{\sum g_i}{\sum h_i + \lambda}
$$
\n(8)
\n
$$
Obj^* = -\frac{1}{2} \sum_{j=1}^J \frac{(\sum g_i)^2}{\sum h_i + \lambda} + \gamma J
$$
\n(9)
\n
$$
Fig. 6. Flowchart of
\nrepresents the optimal solution for the weights,
\nis the score of the loss function.
\nis 'hawks optimization
\nis a heuristic method inspired by the cooperative
$$

where w^* represents the optimal solution for the weights, and *Obj*[∗] is the score of the loss function.

 $w_j^* = -\frac{\sum g_i}{\sum h_i + \lambda}$
 $Obj^* = -\frac{1}{2} \sum_{j=1}^J \frac{(\sum g_i)^2}{\sum h_i + \lambda} + \gamma J$

where w^* represents the optimal solution for the weig

and Obj^* is the score of the loss function.
 B. Harris' hawks optimization

HHO is a heu $w_j^* = -\frac{\sum s_i}{\sum h_i + \lambda}$ (8)
 $Obj^* = -\frac{1}{2} \sum_{j=1}^J \frac{(\sum s_i)^2}{\sum h_i + \lambda} + \gamma J$ (9)

here w^* represents the optimal solution for the weights, As the prey attemy
 obj^* is the score of the loss function.

Harris' hawks optim $\sum h_i + \lambda$
 $Obj^* = -\frac{1}{2} \sum_{j=1}^J \sum_{j=1}^J \sum_{j=1}^R \lambda_j + \lambda^J$ (9)

Where w^* represents the optimal solution for the weights,

and Obj^* is the score of the loss function.

B. *Harris' hawks optimization*

HHO is a heuri $Obj^* = -\frac{1}{2} \sum_{j=1}^{J} \frac{(\sum g_i)^2}{\sum h_i + \lambda} + \gamma J$ (9)

where w^{*} represents the optimal solution for the weights, as the prey attempts

and Obj^* is the score of the loss function.

B. *Harris' hawks optimization E* =

HH $Obj^* = -\frac{1}{2} \sum_{j=1}^{J} \frac{(\sum g_j)^2}{\sum h_i + \lambda} + \gamma J$ (9)

Fig. 6. Flowchart of the HHO Algorith

where w* represents the optimal solution for the weights,

as the prey attempts to decreases. The energy E of the

follows:

B. Ha $Obj^* = -\frac{1}{2} \sum_{j=1}^{N} \sum_{j=1}^{N} \sum_{j=1}^{N} h_j + \lambda^{j}$ (9)

Fig. 6. Flowchart of the HHO Algorithm

where w^* represents the optimal solution for the weights,

and Obj^* is the score of the loss function.

B. Harris' hawk primary phases(exploration and exploitation), which imitate where w^* represents the optimal solution for the weights,
and Obj^* is the score of the loss function.
B. *Harris' hawks optimization*
HHO is a heuristic method inspired by the cooperative
hunting behavior of Harris ha EVALUATE THE STAND INTERT STAND THE STAND THE STATES Are the steaded on the production that the steaders are employed for the exploration of the phase means of the initial which is a heuristic method inspired by the coope and Obj^* is the score of the loss function.

B. Harris' hawks optimization

HHO is a heuristic method inspired by the cooperative

hunting behavior of Harris hawks. It seeks to emulate the

hawk's strategies in searching B. Harris' hawks optimization

HHO is a heuristic method inspired by the cooperative

hunting behavior of Harris hawks. It seeks to emulate the

hawk's strategies in searching for globally optimal solutions.

Figure 6 ill *B. Harris' hawks optimization*

HHO is a heuristic method inspired by the cooperative

hunting behavior of Harris hawks. It seeks to emulate the

hawk's strategies in searching for globally optimal solutions.

Figure 6 i *B. Harris hawks optimization*

HHO is a heuristic method inspired by the cooperative

hawk's strategies in searching for globally optimal solutions.

Figure 6 illustrates the flow of the HHO algorithm. The

HHO algorithm HHO is a heuristic method inspired by the co
hunting behavior of Harris hawks. It seeks to en
hawk's strategies in searching for globally optimal
Figure 6 illustrates the flow of the HHO algori
HHO algorithm divides the h

r atural hunting behaviors of Harris' hawks.

In the exploitation plane, two strategies are employed for

In the exploitation phase,

equiprobable global search for prey. When *P*<0.5, each

when were based on the positio In the exploration phase, two strategies are employed for
an equiprobable global search for prey. When $P<0.5$, each
hawk moves based on the positions of other members and
the prey. And while $P> = 0.5$, the Harris hawks w

$$
x_i(t+1) = \begin{cases} X_{rand}(t) - R_1 | X_{rand} - 2R_2 x_i(t) |, q \ge 0.5 \\ X^*(t) - X_m(t) - R_3(L_b + R_4(U_b - L_b)), q < 0.5 \end{cases}
$$
 (10) Levy flight pattern was used random walk pattern character intersect with occasional lo

average position of the current hawk population. Ub and Lb Xrand is a randomly selected individual from the hawk *X_{rand}* is a randomly selected individual from the hawk
population within the current generation. X_m signifies the
average position of the current hawk population. Ub and Lb
are the upper and lower bounds of the searc **Example 10 Applied Mathematics**
Xrand is a randomly selected individual from the hawk
population within the current generation. X_m signifies the
average position of the current hawk population. Ub and Lb
are the up A **Applied Mathematics**

X_{rand} is a randomly selected individual from the hawk

population within the current generation. X_m signifies the

average position of the current hawk population. Ub and Lb

are the upper and and is a randomly selected individual from the hawk
population within the current generation. X_m signifies the
average position of the current hawk population. Ub and Lb
are the upper and lower bounds of the search rang

follows:

$$
E = 2E_0(1 - \frac{t}{M})\tag{11}
$$

Fig. 6. Flowchart of the HHO Algorithm

Fig. 6. Flowchart of the HHO Algorithm

As the prey attempts to escape, its energy gradually

decreases. The energy E of the escaping prey is defined as

follows:
 $E = 2E_0(1 - \frac{t}{M$ While optimal solution

Fig. 6. Flowchart of the HHO Algorithm

As the prey attempts to escape, its energy gradually

decreases. The energy E of the escaping prey is defined as

follows:
 $E = 2E_0(1 - \frac{t}{M})$ (11)

where E Fig. 6. Flowchart of the HHO Algorithm

As the prey attempts to escape, its energy gradually

decreases. The energy *E* of the escaping prey is defined as

follows:
 $E = 2E_0(1 - \frac{t}{M})$ (11)

where *E*₀ represents the i Fig. 6. Flowchart of the HHO Algorithm

As the prey attempts to escape, its energy gradually

decreases. The energy E of the escaping prey is defined as

follows:
 $E = 2E_0(1 - \frac{t}{M})$ (11)

where E₀ represents the initi Fig. 6. Flowchart of the HHO Algorithm

As the prey attempts to escape, its energy gradually

decreases. The energy E of the escaping prey is defined as

follows:
 $E = 2E_0(1 - \frac{t}{M})$ (11)

where E₀ represents the initi As the prey attempts to escape, its energy gradually
decreases. The energy E of the escaping prey is defined as
follows:
 $E = 2E_0(1 - \frac{t}{M})$ (11)
where E₀ represents the initial escape energy of the prey,
which is a ran As the prey attempts to escape, its energy gradually
creases. The energy E of the escaping prey is defined as
llows:
 $E = 2E_0(1 - \frac{t}{M})$ (11)
nere E_0 represents the initial escape energy of the prey,
inch is a random n decreases. The energy *E* of the escaping prey is defined as follows:
 $E = 2E_0(1 - \frac{t}{M})$ (11)

where E_0 represents the initial escape energy of the prey,

which is a random number between (-1, 1). *M* is the

maximum

follows:
 $E = 2E_0(1 - \frac{t}{M})$ (11)

where E_0 represents the initial escape energy of the prey,

which is a random number between (-1, 1). *M* is the

maximum evolutionary generation of the population, and *t*

denotes $E = 2E_0(1 - \frac{t}{M})$ (11)
where E_0 represents the initial escape energy of the prey,
which is a random number between (-1, 1). *M* is the
maximum evolutionary generation of the population, and *t*
denotes the current ev where E_0 represents the initial escape energy of the prey,
which is a random number between (-1, 1). M is the
maximum evolutionary generation of the population, and t
denotes the current evolutionary generation. If the where E_0 represents the initial escape energy of the prey,
which is a random number between (-1, 1). *M* is the
maximum evolutionary generation of the population, and *t*
denotes the current evolutionary generation. If where E_0 represents the initial escape energy of the prey,
which is a random number between (-1, 1). *M* is the
maximum evolutionary generation of the population, and *t*
denotes the current evolutionary generation. If ich is a random number between (-1, 1). *M* is the aximum evolutionary generation of the population, and *t* notes the current evolutionary generation. If the absolute lue of *E* is greater than 1, the exploration phase i maximum evolutionary generation of the population, and t
denotes the current evolutionary generation. If the absolute
value of E is greater than 1, the exploration phase is engaged.
Otherwise, the exploitation phase is in denotes the current evolutionary generation. If the absolute value of *E* is greater than 1, the exploration phase is engaged. Otherwise, the exploitation phase, is initiated. In the exploitation phase, the HHO algorithm value of *E* is greater than 1, the exploration phase is engaged.
Otherwise, the exploitation phase is initiated.
In the exploitation phase, the HHO algorithm employed
four strategies: soft besiege, hard besiege, progress herwise, the exploitation phase is initiated.
In the exploitation phase, the HHO algorithm employed
ur strategies: soft besiege, hard besiege, progressive rapid
scent with soft besiege, and progressive rapid descent
th ha In the exploitation phase, the HHO algorithm employed
four strategies: soft besiege, hard besiege, progressive rapid
descent with soft besiege, and progressive rapid descent
with hard besiege. We define S_p as the prey e

random walk pattern characterized by a series of short steps

IAENG International Journal of Applied Mathematics
walks in environments where the target's location is *C. HHO-XGBoost*
unknown. Its definition is as follows:
 $\begin{array}{ccc}\n\text{This study utilizes the HHO}\n\end{array}$
 $\begin{array}{ccc}\n\text{Levv} = 0.01 \frac{\mu \sigma}{\sigma}$

1AENG International Journal of Applied Mathematical
\nwalks in environments where the target's location is *C. HHO-XGBoost*
\nunknown. Its definition is as follows:
\n
$$
\begin{bmatrix}\nLey = 0.01 \frac{\mu \sigma}{\sqrt{\beta}} & |x| \frac{\mu \sigma}{\beta} & |x| \frac{\mu \sigma}{\beta}\n\end{bmatrix}
$$
\n
$$
\sigma = \left(\frac{\Gamma(1+\beta) \sin(\frac{\beta \pi}{2})}{\Gamma(1+\beta)\beta 2^{\frac{\beta-1}{2}}} \right)^{\frac{1}{\beta}}
$$
\nwhere *u* and *v* are random values ranging from 0 to 1, and β
\nis set to 1.5.
\nThe four strategies are specified as follows, with each one
\nbeing determined by the specific values of two key parameters: *E* and *S_p*.
\nThe first strategy is characterized by 0.5 $\leq |E| < 1$ and $S_p \geq 0.5$. In this scenario, the prey possesses sufficient energy and attempts to escape. It is encircled by the hawks to deplete its
\nimilarity, followed by a surprise bounce. This behavior can be

 $\left[\Gamma(1+\beta)\beta 2^{(\frac{\beta-1}{2})}\right]$ classificat
positions a
is set to 1.5.
The four strategies are specified as follows, with each one
being determined by the specific values of two key
parameters: *E* and *S_p*.
The first strat parameters: *E* and *S_p*.

The first strategy is characterized by $0.5 \le |E| < 1$ and $S_p \ge$

0.5. In this scenario, the prey possesses sufficient energy and

attempts to escape. It is encircled by the hawks to deplete it

$$
\begin{cases} x_i(t+1) = \Delta x_i(t) - E\left|JX^*(t) - x_i(t)\right| \\ \Delta x_i(t) = X^*(t) - x_i(t) \end{cases}
$$
 (13)

solutions in this phase are defined as follows:
 $x_i(t+1) = \Delta x_i(t) - E\left|JX^*(t) - x_i(t)\right|$ (13)
 $\Delta x_i(t) = X^*(t) - x_i(t)$ (13)

where *J* is the jump intensity of the prey, which possesses a

random value in each iteration.

The secon

$$
x_i(t+1) = X^*(t) - E\left|\Delta x_i(t)\right| \tag{14}
$$

The third strategy is characterized by
$$
0.5 \le |E| < 1
$$
 and Sp
\n 0.5 . In this scenario, the prey has sufficient energy to
\nevade the hawks through rapid dives. Therefore, the position
\nof the current solution can be updated as follows.
\n
$$
x_i(t+1) = \begin{cases} Y = X^*(t) - E \left| JX^*(t) - x_i(t) \right|, F(Y) < F(x_i(t)) \\ Z = Y + S \cdot Levy, F(Z) < F(x_i(t)) \end{cases}
$$
\nwhere *F* is the fitness function, and *S* is a random vector
\nranging in (0, 1).
\nThe fourth strategy can be described by the condition $|E| < \frac{1}{X} \leq 0.5$ and $S_p < 0.5$. In this phase, the prey has low
\nenergy, so the solutions are updated accordingly.
\n
$$
x_i(t+1) = \begin{cases} Y' = X^*(t) - E \left| JX^*(t) - x_m(t) \right|, F(Y') < F(x_i(t)) \\ Z' = Y' + S \cdot Lapu, F(Z') < F(x_i(t)) \end{cases}
$$
\nFigure 7 depicts the proti-

where *F* is the fitness function, and *S* is a random vector
\nranging in (0, 1).
\nThe fourth strategy can be described by the condition
$$
|E|
$$

\n0.5 and $S_p < 0.5$. In this phase, the prey has low
\nenergy, so the solutions are updated accordingly.
\n $x_i(t+1) =\begin{cases}\nY' = X^*(t) - E|JX^*(t) - x_m(t)|, F(Y') < F(x_i(t)) \\
Z' = Y' + S \cdot Levy, F(Z') < F(x_i(t))\n\end{cases}$ \nFig. 7. Flowchart of the HHO-Optimize
\nFigure 7 depicts the proceed
\nXGBoost. During the optimization and se
\nFind the optimal individual an
\nBy evaluating the magnitude of different parameters, the
\nstrategy for HHO optimizing the XGBoost is determined.
\n
\n**Volume 55. Ismo 1. Ionuary 2025 Poqos 118 125**

positions are recorded throughout the training phase. learning rate (LR), gamma (GM), subsample (SP), and data undergoes iterative processes for optimization and **C. HHO-XGBoost**
 C. HHO-XGBoost

This study utilizes the HHO algorithm

performance of XGBoost by tuning fou

learning rate (LR), gamma (GM), subset of Applied Mathematics

HHO-XGBoost

This study utilizes the HHO algorithm to optimize the

rformance of XGBoost by tuning four key parameters:

urning rate (LR), gamma (GM), subsample (SP), and

aximum depth (MD). In the **C.** *HHO-XGBoost*

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learning rate (LR), gamma (GM), subsample (SP), and

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performance of XGBoost by tuning four key parameters:

learning rate (LR), gamma (GM), subsample (SP), and

maximum depth (MD). In the optimization p C. *HHO-XGBoost*

This study utilizes the HHO algorithm to optimize the

performance of XGBoost by tuning four key parameters:

learning rate (LR), gamma (GM), subsample (SP), and

maximum depth (MD). In the optimization p

Figure 7 depicts the procedure of the HHO optimizing initialize the population and set up the convergence curve.
Find the optimal individual and ultimately determine the **EXECT ACTES ARELACTS ARE ARE ASSESS**

Fig. 7. Flowchart of the HHO-Optimized XGBoost Algorithm

Figure 7 depicts the procedure of the HHO optimix

XGBoost. During the optimization process, we nee

initialize the populatio

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IAENG International Journal of Applied Mathe
Step 1: Randomly initialize the population and determine
e positions of the hawks and prey. The positions of the angles of the parameters (LR, GM, SP, and MD) in
SBoost. 2: Ca **IAENG International Journal of Applied Mathematic**

Step 1: Randomly initialize the population and determine

the positions of the hawks and prey. The positions of the

hawks contain the parameters(LR, GM, SP, and MD) in
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the positions of the hawks and prey. The positions of the

hawks contain the parameters(LR, GM, SP, and MD) in **IAENG International Journal of Applied Mathema**

Step 1: Randomly initialize the population and determine

Positions of the hawks and prey. The positions of the

wks contain the parameters(LR, GM, SP, and MD) in

SHOOOSt. **EXENT INTENT INTERT IS AND INTERTATIONAL SET USE OF 1:** Randomly initialize the population and determine
the positions of the hawks and prey. The positions of the
hawks contain the parameters(LR, GM, SP, and MD) in
XGBoos

XGBoost.
Step 2: Calculate and update the positions of the hawks

IAENG International Journal of Applied Mathematics

Step 1: Randomly initialize the population and determine

positions of the hawks and prey. The positions of the

WEGOGNITON RATES FOR

SUBOOSt.

SHOOST 49.59% 90.74%

S **IAENG International Journal of Applied Mathems**

Step 1: Randomly initialize the population and determine

the positions of the hawks and prey. The positions of the

hawks contain the parameters (LR, GM, SP, and MD) in
 IAENG International Journal of Applied Mathematic

Step 1: Randomly initialize the population and determine

the positions of the hawks and prey. The positions of the

hawks contain the parameters(LR, GM, SP, and MD) in calculated. Step 1: Randomly initialize the population and determine

2: positions of the hawks and prey. The positions of the

wks contain the parameters (LR, GM, SP, and MD) in
 $\frac{3B\text{Boost}}{99.2\%}$

Step 2: Calculate and update th Step 1: Randomly initialize the popula
the positions of the hawks and prey. Tl
hawks contain the parameters(LR, GM
XGBoost.
Step 2: Calculate and update the posi
based on the prey's energy and escape pro
Step 3: Use the up

Step 1: Randomly initialize the population and determine

2: positions of the hawks and prey. The positions of the

Step 2: Calculate and update the positions of the hawks

Step 2: Calculate and update the positions of the the positions of the hawks and prey. The positions of the

hawks contain the parameters(LR, GM, SP, and MD) in

XGBoost 94.93% OGBoost

Step 2: Calculate and update the positions of the hawks

Lightebm 97.06% 96

based on hawks contain the parameters(LR, GM, SP, and MD) in

XGBoost $^{60,92\%}$

Step 2: Calculate and update the positions of the hawks

based on the prey's energy and escape probability.

Step 3: Use the updated positions' para XGBoost.

Step 2: Calculate and update the positions of the hawks

Step 2: Calculate and update the positions of the hawks

Step 3: Use the updated positions' parameters as input to

Step 3: Use the updated positions' par Step 2: Calculate and update the positions of the hawks
based on the prey's energy and escape probability.
Step 3: Use the updated positions' parameters as input to
build the XGBoost model, then use the model to predict
re build the XGBoost model, then use the model to presults. Repeat steps 2 and 3 until all positions calculated.

Step 4: Search for the optimal global parameters am

all positions.

Step 5: Before reaching the maximum iterat Example 10.9829

In the optimal global parameters among The hybrid algoritically.

I.e. The hybrid algoritical

Sefore reaching the maximum iteration number, the other algoritical

eferred to as GA

Train the XGBoost mode all positions.

Step 5: Before reaching the maximum iteration number, the other all

completed. Train the XGBoost model with these global the fitness cu

parameters and select the best positions during the iteration proces

Finess of GA Contract September of Section 2.9820

completed. Train the XGBoost model with these global the fitness curves of the parameters and select the best positions during the iteration process. The HHO-

process. T completed. Train the ACDBoost model with these global
process. The HHO-XGBoost
process. Then record its parameters.
Process. The HHO-XGBoost
process. Then record its parameters.
Step 6: Train the XGBoost model by the param parameters. Then record its parameters.

Step 6: Train the XGBoost model by the parameters, then

Step 6: Train the XGBoost model by the parameters, then

use the model to evaluate the final classifier for

identification process. Then tector is parameters.

Step 6: Train the XGBoost model by the parameters, then study, with the fitness value

use the model to evaluate the final classifier for iteration. Compared to other

identification a sign of Train the AGBoost model by the parameters, then

use the model to evaluate the final classifier for the metal conter

iteration. Compared to other

iteration. Compared to other

the mutation and classification.

I GRA Was set to 0.001. The gait data was divided into a 70%

HHO-XGBoost exhibited faster chalentification and elassification.

IV. RESULTS AND DISCUSSION

A. Experimental Setup and Parameter Configuration

All algorithms stabionary stabionary stabionary stabion
appl
IV. RESULTS AND DISCUSSION
A. *Experimental Setup and Parameter Configuration*
All algorithms in this study were implemented in
PyCharm using Python version 3.11.4. The experim IV. RESULTS AND DISCUSSION

Experimental Setup and Parameter Configuration

All algorithms in this study were implemented in

Charm using Python version 3.11.4. The experiments

outing the conducted on a personal computer IV. RESULTS AND DISCUSSION

A. Experimental Setup and Parameter Configuration

All algorithms in this study were implemented in

PyCharm using Python version 3.11.4. The experiments

Setup and Parameter Configuration

PyC A. Experimental Setup and Parameter Configuration

All algorithms in this study were implemented in

PyCharm using Python version 3.11.4. The experiments

were conducted on a personal computer equipped with an

AMD Ryzen A. Experimental Setup and Parameter Configuration

PyCharm using Python version 3.11.4. The experiments

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were conducted on a presental computer equipped with an

AMD R All algorithms in this study were implemented in

PyCharm using Python version 3.11.4. The experiments

were conducted on a personal computer equipped with an

AMD Ryzen 5 5600 6-core processor and 16.0 GB of RAM.

The nu AMD Ryzen 5 5600 6-core processor and 16.0 GB of RAM.

The number of iterations for all algorithms was fixed at 150,

with a population size of 30. The mutation probability of

GA was set to 0.001. The gait data was divid

EVALUATE THE SERVICE CONFIDUTE STRING THE COMPARISON CONTINUITY OF THE SERVICE OF A VARIATION OF THE SERVICE OF THE

with a population size of 30. The mutation probability of

GA was set to 0.001. The gait data was divided into a 70% $\frac{4.9845}{10}$ $\frac{4.09845}{20}$ $\frac{4.09845}{40}$

training set and a 30% testing set.

In the hyperpara GA was set to 0.001. The gait data was divided into a 70% $-0.9845\sqrt{\frac{\text{m} \cdot \text{m} \cdot \text{m} \cdot \text{m} \cdot \text{m}}}$

16 training set and a 30% testing set.

In the hyperparameter tuning of the optimized XGBoost

algorithm, the LR wa training set and a 30% testing set.

In the hyperparameter tuning of the optimized XGBoost

algorithm, the LR was varied between 0.01 and 1, GM

between 0 and 0.1, MD from 4 to 12, and SP was fixed at

0.1. Each algorithm In the hyperparameter tuning of the optimized XGBoost
algorithm, the LR was varied between 0.01 and 1, GM
between 0 and 0.1, MD from 4 to 12, and SP was fixed at
0.1. Each algorithm was executed 10 times on the gait
datas is defined by specific mathematical formulas. By evaluating

intervalue of the results. Algorithm, the LR was varied between 0.01 and 1, GM

between 0 and 0.1, MD from 4 to 12, and SP was fixed at
 0.1 . Each algorithm w Examplementation and the model can be two secured can be the result from Male the result of the model through them, the accuracy of the model can be the model can be the model can be the model through them, the accuracy o between 0 and 0.1, MD from 4 W 12, and 51 was fixed

0.1. Each algorithm was executed 10 times on the $\frac{1}{4}$

dataset to ensure the robustness and reliability of the result

dataset to ensure the robustness and reliab *B. Performance Evaluation Metrics*
Various performance evaluation metrics ex
assessing machine learning models. This study a
accuracy, precision, recall, and F1 score. Depending
application, each of these metrics can prov Performance Evaluation Metrics

Various performance evaluation metrics exist for

COA-XGBoost 0.2580

Suracy, precision, recall, and F1 score. Depending on the

E. Comparison of Algorithm Sta-

policiation, each of these m Example the proposes the control of the control of the control of the same termine evaluation metrics exist for the and same algorithm application, each of these metrics can provide unique for emergency, precision, recall various performance evaluation metrics exist for
accuracy, precision, recall, and F1 score. Depending on the
accuracy, precision, recall, and F1 score. Depending on the
magnification, each of these metrics can provide uni

accuracy, precision, recall, and F1 score. Depending on the E. Comparison of Algorithm Staplication, each of these metrics can provide unique inclusions, each of these metrics is defined by specific mathematical formulas. application, each of these metrics can provide unique To ensure the robustness comparison into the model's performance. Each of these metrics is defined by specific mathematical formulas. By evaluating a HHO-XGBoost algori msignts into the models performance. Each of these metrics
is defined by specific mathematical formulas. By evaluating
the model drowing the model can be the model can be the model through them, the accuracy of the model c is aermed by specific mannematical formulas. By evaluating
the model through them, the accuracy of the model can be
significant variations for dif-
the result from Male 5 acl
C. Classifier Selection
During the initial stag the model through them, the accuracy of the model can be
more accurate and reliable.
C. Classifier Selection
will be result from Male 5
while the result from Male 5
while the result from
mange of algorithms for data classi more accurate and reliable.

C. Classifier Selection

C. Classifier Selection

During the initial stages of our research, we employed a

95.24%. These discrepancies n

range of algorithms for data classification, including study.

Step 3: Use the updated positions' parameters as input to

Step 3: Use the updated positions' parameters as input to

id the XGBoost model, then use the model to predict
 D. Comparison of Optimizatius

Itelated.

Itelate Step 3: Use the updated positions' parameters as input to

build the XGBoost model, then use the model to predict D. Comparison of Optimizatio

results. Repeat steps 2 and 3 until all positions are allevithms (GA, AOA, COA Step 3: before reaching the maximum treation number, the one of a sporting the maximum tend of the step 2, 3, and 4 until iteration stress curves of these algorithms in the AGBoost model by the parameters, then the HHO-XGB TABLE I
 EXECTED TRACES INTERENT CONSULTER CONSULTS
 EXECTED TRACES IN THE TIME
 EXECTED TRACES AND TRACES SET AND ACTLEM
 EXERCT SUBDOOST 95.06% 96.44% 96.68% 6.68
 EXERCT SUBDOOST 97.02% 96.64% 96.85% 1.75
 XG TABLE I

TABLE I

Algorithm Precision Recall F1 Time

NGBoost 94.93% 90.76% 92.47% 40.95

CatBoost 96.92% 96.44% 96.68% 6.65

Lightgbm 97.06% 96.64% 96.85% 1.75

XGBoost 97.22% 96.69% 96.95% 0.35

D. Comparison of Optimiza TABLE I

TABLE I

MGBoost Piession Recall F1 Time

NGBoost 94.93% 90.76% 92.47% 40.95

CatBoost 96.92% 96.44% 96.68% 6.68

Lightgbm 97.06% 96.64% 96.85% 1.75

XGBoost 97.22% 96.69% 96.95% 0.35

D. Comparison of Optimizatio TABLE I

THEOGNITION RATES FOR FOUR ALGORITHMS

MGBoost 94.93% 90.76% 92.47% 40.9S

CatBoost 94.93% 90.76% 92.47% 40.9S

CatBoost 95.92% 96.44% 96.68% 6.6S

Lightgbm 97.06% 96.64% 96.85% 1.7S

XGBoost 97.22% 96.69% 96.95% RECOGNITION RATES FOR FOUR ALGORITHMS

Algorithm Precision Recall F1 Time

NGBoost 94.93% 90.76% 92.47% 40.98

CatBoost 96.92% 96.44% 96.68% 6.68

Lightgbm 97.06% 96.64% 96.85% 1.75

XGBoost 97.22% 96.69% 96.95% 0.38

D. C **Example 11 Fresholom** Freedal From Freedal From Freedal From Freed From CatBoost 96.92% 96.44% 96.68% 6.68 Lightgbm 97.06% 96.64% 96.85% 1.7S XGBoost 97.22% 96.64% 96.85% 1.7S XGBoost 97.22% 96.69% 96.95% 0.35 D. Compari Process. The HHO-XGBoost combination demonstrated
starboost 96.92% 96.44% 96.68% 0.38
Lightgbm 97.06% 96.64% 96.85% 1.75
XGBoost 97.22% 96.69% 96.95% 0.38
D. Comparison of Optimization Algorithms
algorithms (GA, AOA, COA, Lightgbm 97.06% 96.64% 96.85% 1.75

XGBoost 97.22% 96.69% 96.95% 0.35

D. Comparison of Optimization Algorithms

Throughout the study, we integrated four optimization

algorithms (GA, AOA, COA, and HHO) with XGBoost.

The $XGBoost$ 97.22% 96.69% 96.95% 0.35

D. Comparison of Optimization Algorithms

Throughout the study, we integrated four optimization

algorithms (GA, AOA, COA, and HHO) with XGBoost.

The hybrid algorithm resulting from the D. Comparison of Optimization Algorithms
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algorithms (GA, AOA, COA, and HHO) with XGBoost.
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referred to as GA D. Comparison of Optimization Algorithms
Throughout the study, we integrated four optimization
algorithms (GA, AOA, COA, and HHO) with XGBoost.
The hybrid algorithm resulting from the integration of GA is
referred to as GA Example 18 and HHO, we integrated four optimization
algorithms (GA, AOA, COA, and HHO) with XGBoost.
algorithms (GA, AOA, COA, and HHO) with XGBoost.
The hybrid algorithm resulting from the integration of GA is
referred to Infroughout the study, we integrated four optimization
algorithms (GA, AOA, COA, and HHO) with XGBoost.
The hybrid algorithm resulting from the integration of GA is
referred to as GA-XGBoost, with similar designations for algorithms (GA, AOA, COA, and HHO) with XGBoost.
The hybrid algorithm resulting from the integration of GA is
referred to as GA-XGBoost, with similar designations for
the other algorithms, such as the AOA-XGBoost, the
COA

assessing machine learning models. This study employs
application, recall, and F1 score. Depending on the E. Comparison of Algorithm S
application, each of these metrics can provide unique To ensure the robustness of
insig TABLE II

SUBDRET TREAS SELECTION

Algorithm LR GM MD SP

XGBoost 0.1 0 6 1

GA-XGBoost 0.1668 0 12 0.9551

AOA-XGBoost 0.2576 0.0050 11 1

COA-XGBoost 0.2580 0.0298 10 0.5055

HHO-XGBoost 0.5462 0.0692 12 1

E. Comparison COMPARISON OF HYPERPARAMETERS SELECTION

Algorithm LR GM MD SP

XGBoost 0.1 0 6 1

GA-XGBoost 0.2576 0.0050 11 1

COA-XGBoost 0.2580 0.0298 10 0.5055

HHO-XGBoost 0.5462 0.0692 12 1

LE. Comparison of Algorithm Stability
 the result from Male 5 achieved an accuracy of 99.11%, GA-XGBoost 0.1668 0 12 0.9551

AOA-XGBoost 0.2576 0.0050 11 1

COA-XGBoost 0.2580 0.0298 10 0.5055

HHO-XGBoost 0.5462 0.0692 12 1

LE. Comparison of Algorithm Stability

To ensure the robustness of the algorithm and avoid AOA-XGBoost 0.2576 0.0050 11 1

COA-XGBoost 0.2580 0.0298 10 0.5055

HHO-XGBoost 0.5462 0.0692 12 1

E. Comparison of Algorithm Stability

To ensure the robustness of the algorithm and avoid the

potential bias of evaluati COA-XGBoost 0.2880 0.0298 10 0.3058

HHO-XGBoost 0.5462 0.0692 12 1

E. Comparison of Algorithm Stability

To ensure the robustness of the algorithm and avoid the

potential bias of evaluating a single dataset, we applied **E. Comparison of Algorithm Stability**
 E. Comparison of Algorithm Stability

To ensure the robustness of the algorithm and avoid the

potential bias of evaluating a single dataset, we applied the

HHO-XGBoost algorithm E. Comparison of Algorithm Stability
To ensure the robustness of the algorithm and avoid the
potential bias of evaluating a single dataset, we applied the
HHO-XGBoost algorithm to the datasets of 10 different
subjects. As E. Comparison of Algorithm Stability
To ensure the robustness of the algorithm and avoid the
potential bias of evaluating a single dataset, we applied the
HHO-XGBoost algorithm to the datasets of 10 different
subjects. As To ensure the robustness of the algorithm and avoid the
potential bias of evaluating a single dataset, we applied the
HHO-XGBoost algorithm to the datasets of 10 different
subjects. As shown in Table III, the test results potential bias of evaluating a single dataset, we applied the HHO-XGBoost algorithm to the datasets of 10 different subjects. As shown in Table III, the test results indicate significant variations for different individual motion. bjects. As shown in Table III, the test results indicate entificant variations for different individuals. For example, e result from Male 5 achieved an accuracy of 99.11%, ille the result from Male 6 obtained an accuracy significant variations for different individuals. For example,
the result from Male 5 achieved an accuracy of 99.11%,
while the result from Male 6 obtained an accuracy of
95.24%. These discrepancies may stem from differenc

IAENG International Journal of Applied Mathematics
each individual's data is notably significant. Compared to HHO-XGBoost algorithm shows
other algorithms, this optimization technique achieves the in accuracy compared to **IAENG International Journal of Applied Mathematic**
each individual's data is notably significant. Compared to HHO-XGBoost algorithm show
other algorithms, this optimization technique achieves the in accuracy compared to t **EXERY Solution**
 EXERY SOLUTE AND SERVIET SURFER IN A SERVIET SURFER IN THE SAMPLE THE SAMPLE IN A SERVIET SURFER III

The TT and SH states are stability of HHO-XGBoost in gait recognition tasks.

TABLE III

TABLE III
 EXEL TRENC International Journal of Applied Mathemation

each individual's data is notably significant. Compared to HHO-XGBoost algorithm show

other algorithms, this optimization technique achieves the in accuracy compa **IAENG International Journal of Applied Ma**
each individual's data is notably significant. Compared to HHO-XGBoost algo
other algorithms, this optimization technique achieves the in accuracy compare
most substantial improv **IAENG International Journal of A**

notably significant. Compared to HHO-2

timization technique achieves the in accuracy.

ement in accuracy. This finding The T1

receptional performance and The H

it in gait recognition CH individual's data is notably significant. Compared to HHO-XGBo

her algorithms, this optimization technique achieves the in accuracy

ost substantial improvement in accuracy. This finding The TT and the

reformance and

each individual's data is notably significant. Compared to other algorithms, this optimization technique achieves the most substantial improvement in accuracy. This finding			HHO-XGBoost algorithm show in accuracy compared to the or The TT and SH states are suscep					
further underscores the exceptional performance			The HHO-XGBoost algorithm					
stability of HHO-XGBoost in gait recognition tasks.							rates of these two actions by 0.	
	RECOGNITION RATES OF FIVE ALGORITHMS ON DATA FROM TEN TESTERS	TABLE III	the other three algorithms also o in action recognition accuracy					
Testers	XGBoost	GA-XG Boost	AOA-X GBoost	COA-XG Boost	HHO-XG Boost		inferior to that of the HHO-XGE is shown in Figure 11. Overal proposed method remains except	
Male 1	96.40%	96.51%	96.53%	96.49%	96.56%			
Male 2	97.26%	97.38%	97.35%	97.39%	97.44%			
Male 3	98.35%	98.43%	98.45%	98.47%	98.52%			
Male 4	98.87%	98.97%	98.97%	99.00%	99.05%			
Male 5	95.84%	95.92%	95.94%	95.97%	96.01%		98.56%	
Male 6	98.82%	98.90%	98.89%	98.94%	98.99%	100	98.67%	
Female 1	95.91%	96.02%	96.03%	96.05%	96.09%		98.35% 98.52%	
Female 2	98.98%	99.09%	99.11%	99.10%	99.15%	99	98.54	
Female 3	99.24%	99.32%	99.30%	99.36%	99.44%	98		
Female 4	98.75%	98.87%	98.84%	98.89%	98.91%	97		
						$Accuracy(^{0}_{0})$ 96	95.67%	
F. Results and discussion				95	94.83% 95.40%			
	Table IV illustrates the results of various algorithms in			94	94.53% 94.90% 94.92%			
classifying the gait patterns. Compared to other algorithms,			93	94.97%				
the HHO-XGBoost algorithm indicate notable high results in four metrics. The HHO-XGBoost achieves higher in			XGBoost	GA XGBoost AOA_XGBoost				
accuracy, precision, recall, and the F1 score by 0.35%,	0.26% 0.47% and 0.42% then the eviginal VCD cost The			COA XGBoost HHO \mathcal{A} lgorithm				

Male 4 98.87% 98.97% 98.97% 99.90% 99.06% 99.06% Male 6 98.82% 98.99% 98.99% 96.00% 60.90% Female 1 95.91% 96.99% 96.99% 96.99% 96.00% Female 2 98.98% 98.99% 98.99% 98.99% 96.00% 96.00% 96.00% 96.00% 96.00% 96.00% 96.99% Male 6 98.82% 95.94% 99.88% 98.99% 98.99% 100

Female 1 95.91% 96.02% 96.03% 96.03% 96.05% 96.09% 100

Female 2 98.88% 99.09% 99.11% 99.10% 99.16% 96.09% 100

Female 2 98.88% 99.92% 99.30% 99.44% 98.89% 98.91% 99.92% 99.92 Framle 1 95.91% 96.02% 96.03% 96.05% 96.09% 96.09% 100

Female 2 98.88% 99.09% 99.11% 99.10% 99.16% 99.15% 98.91% 99.15% 98.87% 98.87% 98.87% 98.84% 98.89% 9.044% Pemale 4 98.75% 98.87% 98.84% 98.89% 98.91% 99.44% Pemale Female 2 98.98% 99.09% 99.11% 99.10% 99.15% 99.18% 99.18% 99.18% 99.18% 99.18% 99.36% 99.44% 98.89% 99.44% 98.89% 99.44% 98.91% 2.5% 99.91% Female 4 98.75% 98.87% 98.84% 98.89% 98.91% 2.5% 98.91% 2.5% 9.89% 98.91% 2.5% 9. remale 3 99.24% 99.32% 99.30% 99.36% 99.4% 99.36% 99.4% 99.36% 99.4% 98.89% 98.9% 98 F. Results and discussion

Table IV illustrates the results of various algorithms in

classifying the gait patterns. Compared to other algorithms,

the HHO-XGBoost algorithm indicate notable high results

in four metrics. *F. Results and discussion*
Table IV illustrates the results of various algorit
classifying the gait patterns. Compared to other algo
the HHO-XGBoost algorithm indicate notable high
in four metrics. The HHO-XGBoost achieve Ithm indicate notable high results

IO-XGBoost achieves higher in

1, and the F1 score by 0.35%,

than the original XGBoost. The

rmance compared with the other Fig.10. Accura

The HHO-XGBoost algorithm

nance in gait clas ccuracy, precision, recall, and the F1 score by 0.35%,

.36%, 0.47%, and 0.42% than the original XGBoost. The

IHO showed better performance compared with the other

ptimization algorithms. The HHO-XGBoost algorithm

cali

	Algorithm	Accuracv	Precision	Recall	F1 Score		0.0179	0.9531
XGB oost		97.50%	97.05%	96.56%	96.80%	ಕಾ		
	GA-XGBoost	97.78%	97.35%	96.94%	97.15%	.ಇ		
	AOA-XGBoost	97.76%	97.38%	96.96%	97.17%	Φ		
	COA-XGBoost	97.79%	97.37%	96.98%	97.19%	SН	0.0202	0.0010
	HHO-XGBoost	97.85%	97.41%	97.03%	97.22%			

Fig.11. Confusion matrix for HH

Fig.9. Comparison of labels and results

Fig.9. Comparison of labels and results

Fig.9. Comparison of labels and results

Figure 9 shows the recognition results compared with the results i Fig.9. Comparison of labels and results compared with the results indicate that Fig.9. Comparison of labels and results compared with the repognition accuracy and labeled ones. The patterns identified by the HHO-XGBoost fi EVER THE THE TRIGGED ISLAM THE TRIGGED TRIGGED TRIGGED AND THE TRIGGED TRIGGED TRIGGED AND TRIGGED AND TRIGGED ONCE THE TRIGGED ONCE THE TRIGGED ON SIGNAL TRIGGED AND MESS THE PROCEED ON THE TRIGGED ON SIGNAL TRIGGED AND

COA-XG HHO-XG proposed method remains exceptionally strong. **al of Applied Mathematics**

HHO-XGBoost algorithm showed the largest improvement

in accuracy compared to the original XGBoost algorithm.

The TT and SH states are susceptible to classification errors.

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in accuracy compared to the original XGBoost algorithm.
The TT and SH states are susceptible to classification errors.
The HHO-XGBoost algorithm improved the recogniti

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Fredicted label

Fig.11. Confusion matrix for HHO-XGBoost algorithm

The results indicate that the multi-classification model

HHO-XGBoost is capable of accurately identifying f A Predicted label

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I.I. Confusion matrix for HHO-XGBoost algorithm

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The results indicate that the multi-classification model

HHO-XGBoost is capable of accurately identifying four

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HHO-XGBoost is capable of accurately identifying four
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recognition accuracy and practical applicability. This
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results demonstrate that the HHO-XGBoost algorithm
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