CLAIMS

1. A processor-implemented method for classification and quantitative estimation of real-time value of cognitive stress, the method comprising:

obtaining, while a user is engaged in performance of a task, a plurality of non-invasive physiological signals from a plurality of physiological sensors accessible to the user, via one or more hardware processors;

identifying a plurality of feature sets from the plurality of non-invasive physiological signals, via the one or more hardware processors, the plurality of feature sets correlating with the cognitive stress experienced by the user while engaging in the performance of the task; and

predicting, using a regression model, a stress indicator metric comprising a quantitative estimate of the cognitive stress experienced by the user during the performance of the task, via the one or more hardware processors,

wherein, the regression model is trained using the plurality of feature sets, and independently determined quantitative estimates of cognitive stress used as a ground truth to output value of the stress indicator metric,

wherein, the ground truth is determined from keystroke data associated with the performance of keyboard-based tasks comprising navigation of one or more moving objects to at least one target from a plurality of targets, and

wherein determining the quantitative estimate of cognitive stress from the keystrokes comprises:

obtaining the keystroke data during performance of at least one keyboard-based task involving navigating a moving object to a target object out of a plurality of target objects;

determining relative position of the moving object with respect to the ultimate target object during each epoch of the keyboard based task, an epoch associated with the moving object comprises a duration of time available for directing said moving object to the target object, the relative position determined in terms of keystrokes (y_s) made during the performance of keystroke based task in a direction towards the target object and keystrokes

(y_o) away in a direction away from the target object, such that relative position of the target object is $x=y_s-y_o$.

2. The method as claimed in claim 1, wherein the plurality of non-invasive physiological signals comprises Electroencephalogram (EEG) signal to estimate the neural responses of the user, Photoplethysmogram (PPG) to analyze cardiac parameters of the user, and Electrodermal or Galvanic Skin Response (GSR) to determine changes due to variations in skin conductance of the user.

3. The method as claimed in claim 1, further comprising preprocessing the plurality of non-invasive physiological signals in order to reduce corruption of the plurality of non-invasive physiological by noise, reduce intra-user and inter-user variability and decrease computational effort for identifying the plurality of feature steps and predicting the stress indicator metric.

4. The method as claimed in claim 2, wherein identifying the plurality of feature sets from the plurality of non-invasive physiological signals comprises:

extracting a feature set individually from each non-invasive physiological signal of the plurality of non-invasive signals to obtain the plurality of feature sets; and

performing feature reduction on each feature set of the plurality of feature sets to obtain an optimum feature set.

5. The method as claimed in claim 1, further comprising:

defining for each of the epochs during the keyboard-based task a single value of f(t) at each time instant (t=0 to T, T=duration of epoch) timestamp is logged such that:

$f(t) = f(t-1)$ denotes no keystroke at time t

$f(t) = f(t-1) - 1/x$ denotes single keystroke in opposite direction (y_o) at time t

$f(t) = f(t-1) + 1/x$ denotes single keystroke in same direction (y_s) at time t

computing the values of stress indicator metric based on the equation $S = (A - 10B)/T - 0.5$, where, where A represents rewards for persistence and B represents penalties for indecision, and

$$A = \sum_{t=0}^{T} min[f(T), max\{f(t), f(0)\}]$$

$$B = \sum_{t=0}^{T} |min\{\overline{f(t)}, f(0)\}| + max\{f(t), f(T)\} - f(T)$$

6. The method as claimed in claim 1, wherein the regression model is trained using plurality of features sets from each non-invasive physiological signal individually or in combination as predictors and the stress indicator metric *S* as ground truth.

7. The method as claimed in claim 1, further comprising developing, from the plurality of non-invasive physiological signals, a classification model to differentiate between high and low cognitive stress experienced by the user, wherein developing the classification model comprises:

classifying the level of cognitive stress based on the plurality of feature sets obtained from the plurality of non-invasive physiological signals using a feature level fusion and a decision level fusion,

wherein, the feature level fusion of the plurality of feature sets comprises:

accumulating the feature sets associated with the plurality of non-invasive physiological signals to obtain a composite feature set, and

performing feature reduction of the composite feature set,

and wherein, the decision level fusion comprises:

training a plurality of models individually corresponding to each of the plurality of features set from each non-invasive physiological signals as originating from to classify each of the plurality of non-invasive physiological signals as high stress or low stress task(s), and

applying a logical AND operator to the binary classification outcome of the plurality of non-invasive physiological signals obtained from the individual classifiers.

8. A system for classification and quantitative estimation of real-time value of cognitive stress, the system comprising:

one or more memories; and

one or more hardware processors, the one or more memories coupled to the one or more

hardware processors, wherein the one or more hardware processors are capable of executing programmed instructions stored in the one or more memories to:

obtain, while a user is engaged in performance of a task, a plurality of non-invasive physiological signals from a plurality of physiological sensors accessible to the user;

identify a plurality of feature sets from the plurality of non-invasive physiological signals, the plurality of feature sets correlating with the cognitive stress experienced by the user while engaging in the performance of the task; and

predict, using a regression model, a stress indicator metric comprising a quantitative estimate of the cognitive stress experienced by the user during the performance of the task,

wherein, the regression model is trained using the plurality of feature sets and independently determined quantitative estimates of cognitive stress used as a ground truth to output the value of the stress indicator metric,

wherein, the ground truth is determined from keystroke data associated with the performance of keyboard-based tasks comprising navigation of one or more moving objects to at least one target from a plurality of targets, and

wherein to determine the quantitative estimate of the cognitive stress from the keystrokes, the one or more hardware processors are further configured by the instructions to:

obtain the keystroke data during performance of at least one keyboard-based task involving navigating a moving object to a target object out of a plurality of target objects;

determine relative position of the moving object with respect to the ultimate target object during each epoch of the keyboard based task, an epoch associated with the moving object comprises a duration of time available for directing said moving object to the target object, the relative position determined in terms of keystrokes (y_s) made during the performance of keystroke based task in a direction towards the target object and keystrokes (y_o) away in a direction away from the target object, such that relative position of the target object is $x=y_s-y_o$.

9. The system as claimed in claim 8, wherein the plurality of non-invasive physiological signals comprises Electroencephalogram (EEG) signal to estimate the neural responses of the user, Photoplethysmogram (PPG) to analyze cardiac parameters of the user, and

Electrodermal or Galvanic Skin Response (GSR) to determine changes due to variations in skin conductance of the user.

10. The system as claimed in claim 8, wherein the one or more hardware processors are further configured by the instructions to preprocess the plurality of non-invasive physiological signals in order to reduce corruption of the plurality of non-invasive physiological by noise, reduce intra-user and inter-user variability and decrease computational effort for identifying the plurality of feature steps and predicting the stress indicator metric.

11. The system as claimed in claim 10, wherein to identify the plurality of feature sets from the plurality of non-invasive physiological signals, the one or more hardware processors are further configured by the instructions to:

extract a feature set individually from each non-invasive physiological signal of the plurality of non-invasive signals to obtain the plurality of feature sets; and

perform feature reduction on each feature set of the plurality of feature sets to obtain an optimum feature set.

12. The system as claimed in claim 11, wherein the one or more hardware processors are further configured by the instructions to:

define for each of the epochs during the keyboard-based task a single value of f(t) at each time instant (t=0 to T, T=duration of epoch) timestamp is logged such that:

f(t) = f(t-1) denotes no keystroke at time t

f(t) = f (t-1) - 1/x denotes single keystroke in opposite direction (yo) at time t

f(t) = f (t-1) + 1/x denotes single keystroke in same direction (ys) at time t

compute the values of stress indicator metric based on the equation

$S = (A - 10B)/T - 0.5$, where, where A represents rewards for persistence and B represents penalties for indecision,

$$A = \sum_{t=0}^{T} min[f(T), max\{f(t), f(0)\}]$$

$$B = \sum_{t=0}^{T} |min\{f(t), f(0)\}| + max\{f(t), f(T)\} - f(T)$$

13. The system as claimed in claim 8, wherein the one or more hardware processors are further

configured by the instructions to train the regression model using plurality of features sets from each non-invasive physiological signal individually or in combination as predictors and the stress indicator metric S as ground truth.

14. The system as claimed in claim 8, wherein the one or more hardware processors are further configured by the instructions to develop, from the plurality of non-invasive physiological signals, a classification model to differentiate between high and low cognitive stress experienced by the user, and wherein to develop the classification model, the one or more hardware processors are further configured by the instructions to:

classify the level of cognitive stress based on the plurality of feature sets obtained from the plurality of non-invasive physiological signals using a feature level fusion and a decision level fusion,

wherein, to perform the feature level fusion of the plurality of feature sets, wherein the one or more hardware processors are further configured by the instructions to:

accumulate the feature sets associated with the plurality of non-invasive physiological signals to obtain a composite feature set, and

perform feature reduction of the composite feature set,

and wherein, the decision level fusion comprises:

train a plurality of models individually corresponding to each of the plurality of features set from each non-invasive physiological signals as originating from to classify each of the plurality of non-invasive physiological signals as high stress or low stress task(s), and

apply a logical AND operator to the binary classification outcome of the plurality of non-invasive physiological signals obtained from the individual classifiers.

15. A non-transitory computer-readable medium having embodied thereon a computer program for executing a method for classification and quantitative estimation of real-time value of cognitive stress, the method comprising:

obtaining, while a user is engaged in performance of a task, a plurality of non-invasive physiological signals from a plurality of physiological sensors accessible to the user, via one or more hardware processors;

identifying a plurality of feature sets from the plurality of non-invasive physiological signals, via the one or more hardware processors, the plurality of feature sets correlating with the cognitive stress experienced by the user while engaging in the performance of the task; and

predicting, using a regression model, a stress indicator metric comprising a quantitative estimate of the cognitive stress experienced by the user during the performance of the task, via the one or more hardware processors,

wherein, the regression model is trained using the plurality of feature sets, and independently determined quantitative estimates of cognitive stress used as a ground truth to output value of the stress indicator metric,

wherein, the ground truth is determined from keystroke data associated with the performance of keyboard-based tasks comprising navigation of one or more moving objects to at least one target from a plurality of targets, and

wherein determining the quantitative estimation of cognitive stress from the keystrokes comprises:

obtaining the keystroke data during performance of at least one keyboard-based task involving navigating a moving object to a target object out of a plurality of target objects;

determining relative position of the moving object with respect to the ultimate target object during each epoch of the keyboard based task, an epoch associated with the moving object comprises a duration of time available for directing said moving object to the target object, the relative position determined in terms of keystrokes (y_s) made during the performance of keystroke based task in a direction towards the target object and keystrokes (y_o) away in a direction away from the target object, such that relative position of the target object is $x=y_s-y_o$.