# USING PREDICTIVE ANALYTICS TO IMPROVE SURVEILLANCE OF HEAT-RELATED ILLNESS DURING MILITARY TRAINING

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**Abstract**

**Background:** Heat-related illnesses are a critical concern for military personnel, especially those unfamiliar with hot climate regions. The Royal Thai Army (RTA) implements a 10-week military training program encompassing four phases: (1) Heat acclimatization training, (2) Combat fundamentals and unarmed combat training, (3) Armed combat training and tactical training, and (4) Field training exercise and evaluations.

**Objective:** This study aimed to conduct a predictive analysis of heat-related illnesses to enhance prevention programs.

**Methods:** The study utilized secondary data from the RTA Medical Department, incorporating variables such as age, occupation, education, underlying diseases, smoking and alcohol consumption, sleep duration, exercise, medication history, body mass index (BMI), weight loss, body temperature, dark urine, heat rash, and environmental humidity. Multiple machine learning algorithms were employed to develop predictive models.

**Results:** The samples comprised 809 male recruits (103,051 encounters) with an average age of 22. Approximately 12% of the recruits had a BMI ≥30 kg/m$^2$, while nearly 70% and 90% reported tobacco use and alcohol consumption in the past 12 months, respectively. Among the recruits, 16% reported substance use within the preceding 30 days. The eXtreme Gradient Boosting (XGB) model achieved 91% accuracy in predicting heat-related illnesses before Phase 2. The top five predictive variables were Lopburi Province (central region), Songkhla Province (southern region), and Bangkok (capital city), sleep duration before joining military training (hours), and age (years).

**Conclusion:** This study, which applied machine learning techniques to predict heat-related illnesses among Thai recruits, can potentially impact the health and training of military personnel. The comparative analysis of various algorithms identified the XGB model as the optimal performer in predicting heat-related illnesses during the combat fundamentals and unarmed combat training phase. However, it is essential to note that further study is needed to enhance the applicability of our predictive model, which includes expanding its use to new cohorts of Thai conscripts, underscoring our research's ongoing nature.

**Keywords:** heat-related illnesses, heat stroke, machine learning, military, prediction

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## Introduction

Heat-related illnesses encompass a range of symptoms that arise from the excessive accumulation of body heat, typically due to prolonged exposure to elevated ambient temperatures or intense physical activity.[1] Prolonged overheating can impair the thermoregulatory mechanism of the hypothalamus and other vital organs, such as the heart, kidneys, liver, muscles, and brain.[2, 3] Clinical manifestations such as heat rash, edema, cramping, tetany, syncope, heat exhaustion, and heat stroke are observed within the spectrum of heat-related illnesses. Among these conditions, heat stroke is the most severe, with the potential to cause fatalities and organ failure. According to the international classification of heat-related illnesses, heat cramps, syncope, heat exhaustion, and heat stroke are categorized as severe.[2, 4, 5]

Heat stroke is characterized by a core body temperature surpassing 40 °C, consequent to exposure to a hot and humid environment, often accompanied by altered consciousness. Delayed treatment significantly amplifies the risks of severe complications and escalates the fatality rate by up to 50%.[6, 7] In a report issued by the US Armed Forces Health Surveillance Division in 2021, 488 incidents of heat stroke and 1,864 cases of heat exhaustion were reported during the year. In the Central Command Area of Responsibility, i.e., Southwest Asia/Middle East, 312 heat illnesses were diagnosed and treated over the five-year surveillance period, with heat stroke constituting 6.4% of these cases.[8] In Thailand, heat-related illnesses represent a pressing public health concern, particularly concerning military operations. However, studies reporting the incidence of heat-related illnesses in the country remain limited. According to the Bureau of Occupational and Environmental Diseases Thailand, the annual rate of heat-related illness in 2018 was 0.12 per 100,000 population.[9]

Contributing factors to heat stroke can be categorized into individual and environmental determinants within the purview of our study. Individual factors encompass variables such as obesity, dehydration, heat intolerance, sleep deprivation, acute illness, medication use, substance addiction, alcohol consumption, skin disorders, age, and prior history of heat stroke.[10-13] Environmental factors encompass ambient temperature, humidity levels, exercise intensity, and participation in uncontrolled physically demanding activities.[6, 14-17] Timely intervention for heat stroke is crucial to prevent severe complications, including organ dysfunction and mortality. Initial management focuses on reducing core temperature below 39 °C within 30 minutes, followed by rapid transfer to a medical facility.[18] Considering the preventability and predictability of heat stroke, our study emphasized primary prevention strategies to safeguard the health of military recruits. This study aimed to develop predictive analytics models that help military trainers adjust training programs for high-risk trainees, enabling early detection of potential heat-related illnesses during the initial five weeks encompassing the combat fundamentals and unarmed combat training phase.

## Methods

*Database and Data Collection*

In 2009, the Royal Thai Army (RTA) initiated the RTA Heat-Related Illnesses Prevention Program for conscripts in response to annual reports of heat-related illnesses during the 10-week basic military training program. Initially, the program focused on environmental factors such as temperature (in Celsius) and humidity. The RTA used flag signs representing different humidity ranges to regulate and guide everyone's training duration and water consumption. In 2012, the RTA identified additional factors associated with heat-related illnesses, including body mass index (BMI), acute respiratory and gastrointestinal illnesses, and illicit drug usage. A screening process was implemented to identify conscripts at high risk of heat-related illnesses, and lower-intensity training was provided to these groups. Following a high incidence rate of cases, the RTA adjusted its protocols and prevention program to enhance surveillance and outcomes. The revised program consisted of four phases: (1) Heat acclimatization training phase, (2) Combat fundamentals and unarmed combat training phase, (3) Armed combat training and tactical training phase, and (4) Field training exercise and evaluation phase. Furthermore, a specific protocol was added for conscripts with a BMI over 30 kg/m² to enhance the surveillance program.

Data collection for this study was conducted by the RTA Medical Department, utilizing standardized questionnaires administered to all conscripts who provided signed informed consent during the 10-week basic military training program annually since 2009. The questionnaires covered various aspects, including environmental factors, individual factors, unit information, and daily observations. Well-trained military trainers measured wet- and dry-bulb temperatures in the training areas at 7:00 am, 11:00 am, 1:00 pm, and 4:00 pm on weekdays. Relative humidity was calculated based on a standard relative humidity table.[19] For our study, we utilized secondary data from the RTA Medical Department database, specifically from May to July 2013, with the approval of the Institutional Review Board of the Royal Thai Army Medical Department (S055h/61_Exp).

The collected data encompassed various conscript characteristics, including age, body weight (kilograms), height (in centimeters), underlying diseases, occupation, education, income, smoking and alcohol consumption habits, drug usage, exercise patterns, and workplace environment. We included temperature and humidity measurements four times a day regarding environmental factors. Daily vital information such as body temperature, weight, and signs and symptoms including fever, common cold, sore throat, headache, diarrhea, heat rash, heat edema, heat cramp, heat tetany, heat syncope, heat exhaustion, and urine color (ranging from light yellow to dark brown) were also included in the dataset.

*Experimental Design and Data Analysis*

Previous studies on heat-related illnesses have explored associated factors using multivariate statistical analysis. More recently, machine learning (ML) and deep learning (DL) techniques have emerged as practical tools for disease prediction. ML algorithms have been employed to predict hospital readmission,[20, 21] DL models have been utilized for skin cancer identification, [22] and DL algorithms have been developed to diagnose diabetic retinopathy from retinal images.[23] In this research, we leveraged ML and DL algorithms to construct predictive models to assist conscript supervisors in forecasting heat-related illnesses during training, aiming to reduce incidence rates and associated complications. We employed various methods, from traditional ML to DL algorithms. The ML methods employed encompassed the generalized linear model (GLM),[24] k-nearest neighbors (kNN), [25] random forest (RF),[26] and eXtreme gradient boosting (XBG).[27] The DL methods comprised the deep neural network (DNN)[28] and the convolutional neural network (CNN).[29] The selected methods are expected to yield meaningful predictive capabilities.

The primary focus of this study was to predict heat-related illnesses, excluding heat rash, during the heat acclimatization training phase (Phase 1) and the combat fundamentals and unarmed combat training phase (Phase 2). Predicted groups of conscripts were then transferred to adjusted training programs to prevent incidents proactively. A descriptive analysis was conducted to characterize the study population. Following data preprocessing, the dataset was divided into a 70:30 ratio for training and testing sets. To compare accuracy, sensitivity, specificity, and the area under the receiver operating characteristic curve (AUC), we performed 10-fold cross-validation with different models. Given the imbalanced nature of the dataset, we employed the Synthetic Minority Over-sampling Technique (SMOTE)[30] on the training set to address this issue before fitting the models. Model performance was validated using a confusion matrix, and measures such as sensitivity, specificity, positive predictive value (PPV), negative predictive value (NPV), and

AUC were computed. Subsequently, we selected the model with the best performance without overfitting to continue the analysis. The analysis was primarily conducted using the R 3.4.2 programming language, with the assistance of the Caret (31) and Keras (32) packages.

**Results**

A total of 809 male conscripts (103,051 encounters) aged over 22 years were included in this study. Most of the study population had normal weight, while 11.9% of the subjects had a BMI ≥30 kg/$m^2$. Approximately 70% and 90% of the conscripts reported smoking and alcohol consumption in the past 12 months, respectively. Among those who consumed alcohol, 77% reported drinking alcohol within the 30 days preceding the training. Most conscripts had no underlying diseases, although some reported a history of allergy/asthma (7.7%), headache/migraine (4.7%), and anemia/thalassemia (1.61%). In terms of medication history in the past 30 days, 127 conscripts (15.7%) reported using substances **(Table 1).** Data were collected from various regions, including Chiang Mai Province (northern region), Ubon Ratchathani Province (northeastern region), Lopburi Province (central region), Songkhla Province (southern region), and Bangkok (capital city). Comparing these regions, the highest incidence of heat-related illnesses was observed in Chiang Mai Province (22 cases) and Songkhla Province (21 cases). In contrast, Lopburi Province had no reported cases and the lowest average humidity **(Table 2).**

To determine the optimal performance of our predictive models, we employed three approaches: (1) predicting heat-related illnesses before Phase 2, (2) predicting heat-related illnesses during Phase 2, and (3) predicting and classifying heat-related illness incidence during both Phase 1 and Phase 2. The third approach yielded four classification outcomes: (1) no incidence in both phases, (2) incidence in Phase 1 but no incidence in Phase 2, (3) no incidence in Phase 1 but incidence in Phase 2, and (4) incidence in both phases. Following the application of multiple ML and DL algorithms using the three approaches, the performance of each model was assessed and reported in **Table 3.** Considering the training program's different periods, we selected the first approach, which allows for timely intervention for new conscripts. The results indicated that the XBG and RF models demonstrated the best performance, followed by the DNN model.

**Table 1.** Characteristics of participants (N=809)

| | n | % |
|---|---|---|
| **Age** | 21.550.73(21.00-29.00) | |
| **BMI (before training, kg/$m^2$)*** | | |
| 18.5 | 76 | 9.39 |
| 18.5-22.9 | 42 | 5.19 |
| 23.0-24.9 | 490 | 60.57 |
| 25.0-29.9 | 105 | 12.98 |
| 30 | 96 | 11.87 |
| **Occupation** | | |
| Unemployed | 63 | 7.79 |
| Student | 118 | 14.59 |
| Agriculturist/Farmer | 231 | 28.55 |
| Office employee | 194 | 23.98 |
| Others | 203 | 25.09 |

**Table 1.** Characteristics of participants (N=809) (Cont.)

| | n | % |
|---|---|---|
| **Education** | | |
| Primary school and lower | 155 | 19.16 |
| Middle school | 290 | 35.85 |
| Secondary school | 168 | 20.77 |
| Higher than secondary school | 196 | 24.22 |
| **Smoking in the past 12 months** | | |
| Never | 195 | 24.10 |
| Ex-smoke | 56 | 6.92 |
| Smoke | 558 | 68.97 |
| **Alcohol drinking in the past 12 months** | | |
| Never | 52 | 6.43 |
| No | 64 | 7.91 |
| Yes | 693 | 85.66 |
| **Alcohol drinking in the past 30 days** | | |
| No | 185 | 22.87 |
| Yes | 624 | 77.13 |
| **Underlying diseases** | | |
| No underlying disease | 574 | 70.95 |
| Allergy/Asthma | 62 | 7.66 |
| Headache/Migraine | 38 | 4.70 |
| Anemia/Thalassemia | 13 | 1.61 |
| **Medications in the past 30 days** | | |
| No medications | 264 | 32.63 |
| Substances | 127 | 15.70 |
| NSAIDs | 103 | 12.73 |
| Diuretics | 21 | 2.60 |
| Sedative | 18 | 2.22 |

*WHO/IASO/IOTF. The Asia-Pacific perspective: Redefining obesity and its treatment. Health Communications Australia: Melbourne, 2000

**Table 2.** Characteristics of training area in Thailand

| Province | Region | Average Temperature (Celsius)* | Average humidity (%)* | No. of cases |
|---|---|---|---|---|
| Lopburi | Central | 33.6 | 53.8 | 0 |
| Ubon Ratchathani | Northeastern | 31.8 | 60.5 | 9 |
| Chiang Mai | Northern | 32.2 | 51.5 | 22 |
| Songkhla | Southern | 31.6 | 67.6 | 21 |
| Bangkok | Capital city | 32.4 | 59.3 | 1 |

*Temperature and humidity at 7:00 am, 11:00 am, 1:00 pm, and 4:00 pm on weekdays during the 10-week training

**Table 3.** Performance of machine learning and deep learning models

| Models | Accuracy (95%CI) | AUC | Sensitivity | Specificity |
|---|---|---|---|---|
| **First Approach (Before Phase 2)** | | | | |
| XGB | 0.91 (0.85, 0.94) | 0.73 | 0.39 | 0.94 |
| RF | 0.91 (0.85, 0.94) | 0.81 | 0.31 | 0.94 |
| kNN | 0.81 (0.75, 0.85) | 0.76 | 0.46 | 0.83 |
| GLM | 0.83 (0.77, 0.87) | 0.77 | 0.23 | 0.85 |
| DNN | 0.89 (0.85, 0.93) | 0.87 | 0.57 | 0.91 |
| CNN | 0.53 (0.47, 0.60) | 0.62 | 0.79 | 0.52 |
| **Second Approach (During Phase 2)** | | | | |
| XGB | 0.80 (0.75, 0.85) | 0.73 | 0.33 | 0.83 |
| RF | 0.80 (0.74, 0.85) | 0.80 | 0.47 | 0.82 |
| kNN | 0.71 (0.64, 0.76) | 0.76 | 0.47 | 0.72 |
| GLM | 0.78 (0.72, 0.83) | 0.76 | 0.47 | 0.80 |
| DNN | 0.84 (0.79, 0.88) | 0.79 | 0.38 | 0.87 |
| CNN | 0.68 (0.62, 0.74) | 0.69 | 0.56 | 0.68 |
| **Third Approach (During both Phase 1 and 2)**** | | | | |
| XGB | 0.86 (0.81, 0.90) | 0.74 | | |
| RF | 0.78 (0.72, 0.83) | 0.78 | | |
| kNN | 0.66 (0.60, 0.72) | 0.74 | | |

** Multiclass classification

eXtreme gradient boosting (XBG), random forest (RF), k-nearest neighbors (kNN), generalized linear model (GLM), deep neural network (DNN) and convolutional neural network (CNN).

*eXtreme Gradient Boosting (XGB)*

The accuracy, sensitivity, specificity, positive predictive value (precision), negative predictive value, and AUC of the XGB model, as determined through 10-fold cross-validation, were 0.91(95% CI: 0.85, 0.94), 0.39, 0.94, 0.26, 0.96, and 0.75, respectively. The variable importance analysis, presented in **Figure 1**, revealed that Lopburi Province, Songkhla Province, sleep duration before joining military training (in hours), Bangkok, and age (in years) were the top five most important attributes. Notably, certain preventable features, such as experiencing dark urine during the second week of training and having a history of dermatitis, emerged as interesting variables. Dark urine indicates severe dehydration and rhabdomyolysis, while dermatitis can affect skin thermoregulation, albeit to varying degrees of severity. Some of these important variables are preventable and could be utilized as inclusion criteria for adjusted training programs or intervention groups.

*Random Forest (RF)*

The RF model demonstrated similar performance to the XGB model, with an accuracy, sensitivity, specificity, positive predictive value (precision), negative predictive value, and AUC of 0.91 (95%CI: 0.85, 0.94), 0.39, 0.94, 0.21, 0.96, and 0.81, respectively, as determined through 10-fold cross-validation. The top five most important attributes identified by the RF model were Lopburi province, Songkhla province, drinking alcohol 2-3 times per week within the past 30 days, age (in years), and history of decongestant usage in the past 30 days **(Figure 2).**

*Common Findings Among Machine Learning Models*

When comparing the variable importance between the XGB, RF, kNN, and GLM models, we observed a common finding among the top five attributes in each model, namely, Songkhla province, which exhibited a high incidence of heat-related illnesses. Eight attributes were

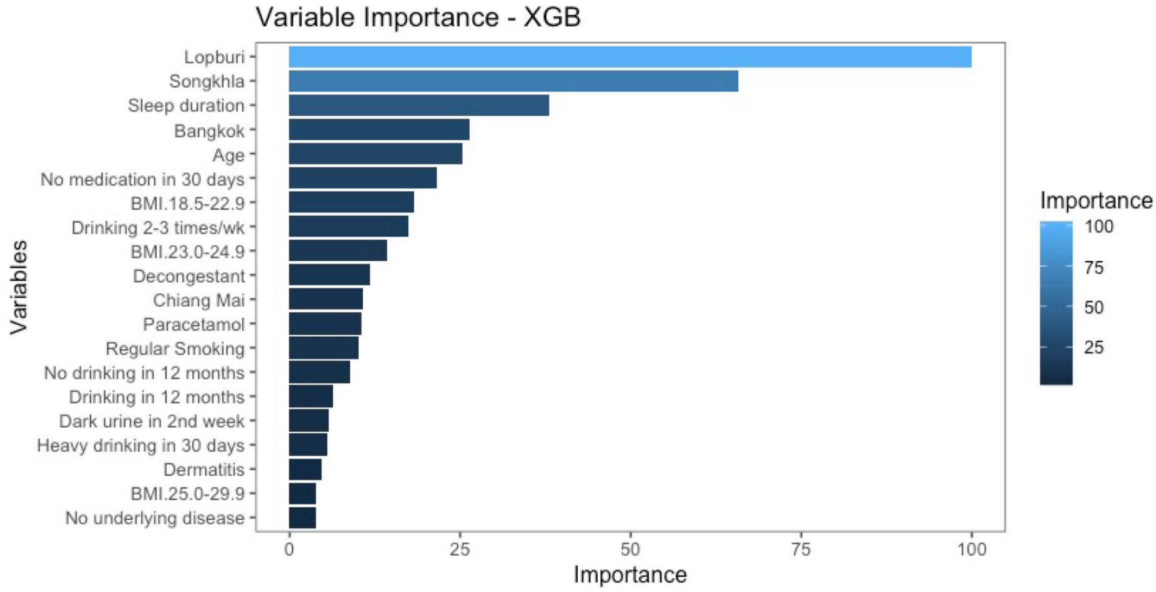


**Fig 1.** Top 20 variable importance of the eXtreme Gradient Boosting (XGB) model.

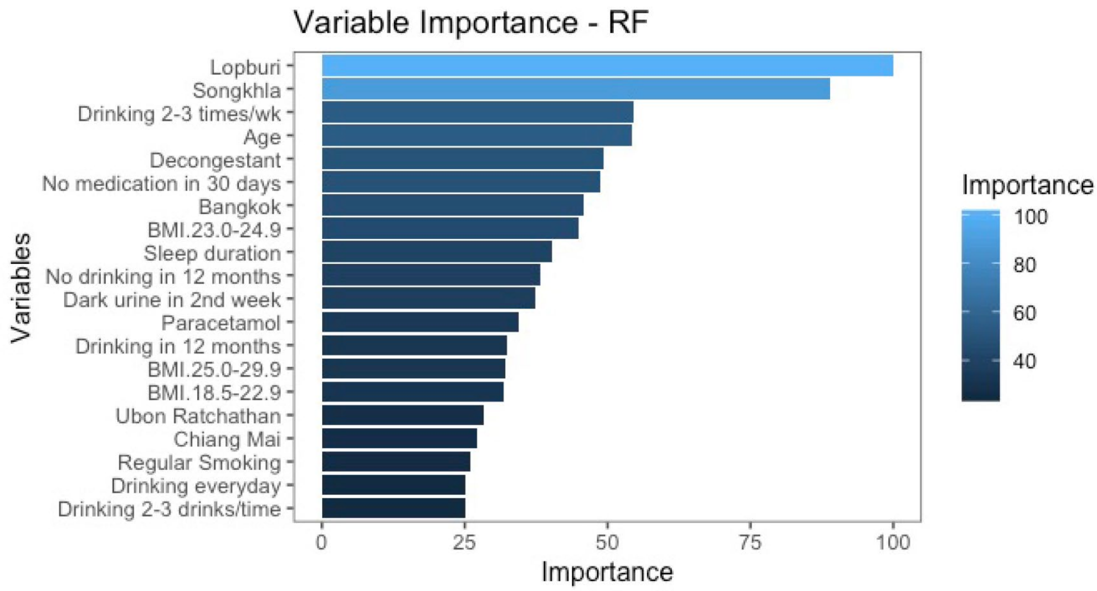


**Fig 2.** Top 20 variable importance of the Random Forest (RF) model.

commonly found among the top 20, including Songkhla, Bangkok, no medication usage, BMI 18.5-22.9 kg/m$^2$, drinking alcohol 2-3 times per week within the past 30 days, BMI 23.0-24.9 kg/m$^2$, taking paracetamol in the past 30 days, and alcohol consumption in the past 12 months. However, all predictors were utilized to achieve the best performance of our predictive models.

*Deep Neural Network (DNN)*

The DNN model exhibited accuracy, sensitivity, specificity, precision, negative predictive value, and AUC of 0.89 (95%CI: 0.85, 0.93), 0.57, 0.91, 0.29, 0.97, and 0.87, respectively. Deep learning is often considered a "black box" due to its complex interpretability. Given the small dataset with imbalanced classes, the performance of the DL model may not be as effective and may be prone to overfitting. Nevertheless, deep learning remains a robust algorithm for medical research, particularly in imaging recognition, automated interpretation, and treatment pathway selection. [33]

**Discussion**

Our study represents the first use of the Royal Thai Army conscript database for predictive analysis, employing machine learning algorithms to enhance the surveillance and prevention of heat-related illnesses in military training programs. Heatstroke is a condition that can be predicted and prevented, but underdiagnosis and improper management can lead to severe complications and even death. It is challenging to detect heat-related illnesses as they can be easily confused with other infectious diseases like the flu, emphasizing the importance of raising awareness among supervisors who train new conscripts. Over the years, efforts at all levels of the organization have reduced the incidence of heat-related illnesses. However, the ultimate goal is to minimize these illnesses' occurrence and associated complications. Applying machine learning algorithms demonstrates the potential of predictive models to achieve reasonably high performance in this context.

Our approach was designed to identify high-risk participants early and provide preventive interventions. Phase 1 of our training program, the heat acclimatization training phase, spans the first two weeks, helping trainees adjust to the new environment and physical activity. Phase 2, the combat fundamentals and unarmed combat training phase, begins in the third week and lasts until the fifth week, involving more intense physical activity. Our records indicated high heat-related illnesses during Phase 1 and Phase 2. Therefore, we aimed to predict the occurrence of these illnesses before Phase 2 and implement adjusted training programs for the identified high-risk group. By the end of the 10-week program, we anticipated reducing the incidence of heat-related illnesses.

Our machine learning models achieved 91% accuracy in predicting heat-related illnesses before Phase 2, indicating that they can effectively contribute to preventing future cases of the disease. Since assigning army doctors to every basic training unit is not feasible, the machine learning model can play a role in the underestimated prevention of heat-related illnesses and provide decision support to the supervisors of the basic training program. As part of future research, we aim to validate our model by applying predictive models to new conscripts and evaluating the incidence of heat-related illnesses, including heat edema, heat cramp, heat tetany, heat syncope, heat exhaustion, and heatstroke, at the end of the program. Furthermore, expanding the study's sample size will enhance the model's performance.

The XGB and RF models are tree-based methods but differ in how trees are constructed. XGB builds trees iteratively, reducing errors by reweighting examples for each subsequent tree. It employs techniques such as regularizing base trees, approximate split finding, weighted quantile sketch, sparsity-aware split finding, and cache-aware block structure for out-of-core computation to prevent overfitting.[27] Conversely, RF is a tree-based algorithm that splits each tree node using a subset of random predictors. This strategy reduces overfitting issues and demonstrates strong performance compared to other classifiers like discriminant analysis, SVM, and neural networks.[34] Each tree provides a classification vote in a random forest, and the majority vote from all classification trees determines the final result. The number of trees (nTree) is crucial for obtaining a well-performing model, stable variable importance, and proximity measures. However, when dealing with large datasets, RF may require significant memory resources, and training can be time-consuming.

Comparing machine learning and deep learning methods, the former offers a better explanation of the analysis process and more reasonable conclusions. In contrast, deep learning models, such as neural networks, are often considered "black-box" models due to their lack of interpretability. In our study, traditional machine learning outperformed deep learning, likely due to the small dataset, and provided actionable insights for military training. Nonetheless, both approaches have their value, and deep learning, despite its limitations and tendency to overfit with small datasets, remains highly valuable in domains such as image recognition and automated interpretation. In our study, the DNN model exhibited better performance than the CNN model, which may be attributed to the small dataset not being well-suited for the CNN algorithm. However, CNN excels in tasks involving imaging data.

This study encountered several limitations that should be considered. First, the dataset used for model development was collected from a specific subset of conscripts within the Royal Thai Army, which may limit the generalizability of the findings to other populations or military settings with different environmental conditions or training protocols. Second, the imbalanced dataset of heat-related illness cases may also limit the robustness of the machine learning and deep learning models. Although techniques like SMOTE were employed to address the imbalance, the models' predictive performance might still be affected. Future studies should aim to expand the dataset and explore more interpretable models to enhance practical applicability.

## Conclusion

In this study, we conducted the first analysis utilizing machine learning and deep learning techniques to predict heat-related illnesses among conscripts. Our findings demonstrated that the eXtreme Gradient Boosting (XGB) and Random Forest (RF) models achieved the highest accuracy in forecasting heat-related illnesses during Phase 2 of the military training program (from the third to the fifth week). Notably, the XGB model identified several influential attributes, including the province of Lopburi, Songkhla, and Bangkok, pre-training sleep duration, and age, emphasizing their significance in the prediction process. Moreover, including regional factors among the top 20 variables suggests the necessity of examining training program structures across different regions alongside environmental temperature and humidity considerations. To further enhance the applicability of our predictive model, future research should involve implementing our approach on new cohorts of Thai conscripts. Additionally, expanding the dataset's sample size would contribute to refining the efficacy of machine learning and deep learning models. By leveraging these advances, the Royal Thai Army can proactively mitigate the incidence of heat-related illnesses and protect the well-being of its soldiers, thereby ensuring the success of military training programs.

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## Authors' Contributions

All authors contributed to the study's conception and design. PN performed material preparation, data collection, and analysis, wrote the first draft of the manuscript, and all authors commented on previous versions. All authors read and approved the final manuscript.

## References

1. Atha WF. Heat-Related Illness. Emerg Med Clin North Am 2013; 31: 1097-108. https://doi.org/10.1016/j.emc.2013.07.012.
2. Bouchama A, Knochel JP. Heat Stroke. N Engl J Med 2002; 346: 1978-88. https://doi.org/10.1056/NEJMra011089.
3. Epstein Y, Roberts WO. The pathophysiology of heat stroke: an integrative view of the final common pathway. Scand J Med Sci Sports 2011; 21: 742-8. https://doi.org/10.1111/j.1600-0838.2011.01333.x.
4. Yamamoto T, Fujita M, Oda Y, Todani M, Hifumi T, Kondo Y, et al. Evaluation of a novel classification of heat-related illnesses: A multicentre observational study (heat stroke study 2012). Int J Environ Res Public Health 2018; 15: 1962. https://doi.org/10.3390/ijerph15091962.
5. Bouchama A. Prognostic factors in heat wave–related deaths, a meta-analysis. Arch Intern Med 2007; 167: 2170. https://doi.org/10.1001/archinte.167.20.ira70009.
6. People's Liberation Army Professional Committee of Critical Care Medicine. Expert consensus on standardized diagnosis and treatment for heat stroke. Mil Med Res 2016; 3: 1. https://doi.org/10.1186/s40779-015-0056-z.

7. Casa DJ, Armstrong LE, Ganio MS, Yeargin SW. Exertional heat stroke in competitive athletes: Curr Sports Med Rep 2005; 4: 309–17.https://doi.org/10.1097/01.CSMR.0000306292.64954.da.
8. Williams V, Oh G-T. Update: heat illness, active component, US Armed Forces, 2021. MSMR 2022; 29: 8–14.
9. Kiatkitroj K, Arphorn S, Tangtong C, Maruo SJ, Ishimaru T. Risk factors associated with heat-related illness among sugarcane farmers in Thailand. Ind Health 2021; 60: 447–58. https://doi.org/10.2486/indhealth.2021-0161.
10. Gardner JW, Kark JA, Karnei K, Sanborn JS, Gastaldo E, Burr P, et al. Risk factors predicting exertional heat illness in male Marine Corps recruits. Med Sci Sports Exerc 1996; 28: 939-44.https://doi.org/10.1097/00005768-199608000-00001.
11. Kim S-H, Jo S-N, Myung H-N, Jang J-Y. The effect of pre-existing medical conditions on heat stroke during hot weather in South Korea. Environ Res 2014; 133: 246-52. https://doi.org/10.1016/j.envres.2014.06.003.
12. Sawka MN, Gonzalez RR, Pandolf KB. Effects of sleep deprivation on thermoregulation during exercise. Am J Physiol 1984; 246: R72-77. https://doi.org/10.1152/ajpregu.1984.246.1.R72.
13. Martinez M, Devenport L, Saussy J, Martinez J. Drug-associated heat stroke. South Med J 2002; 95: 799–802.
14. Coris EE, Ramirez AM, Van Durme DJ. Heat illness in athletes: the dangerous combination of heat, humidity and exercise. Sports Med Auckl NZ 2004; 34: 9-16. https://doi.org/10.2165/00007256-200434010-00002.
15. Cleary M. Predisposing risk factors on susceptibility to exertional heat illness: clinical decision-making considerations. J Sport Rehabil 2007; 16: 204-14. https://doi.org/10.1123/jsr.16.3.204.
16. Bedno SA, Urban N, Boivin MR, Cowan DN. Fitness, obesity and risk of heat illness among army trainees. Occup Med Oxf Engl 2014; 64: 461-7. https://doi.org/10.1093/occmed/kqu062.
17. American College of Sports Medicine, Armstrong LE, Casa DJ, Millard-Stafford M, Moran DS, Pyne SW, et al. American College of Sports Medicine position stand. Exertional heat illness during training and competition. Med Sci Sports Exerc 2007; 39: 556–72. https://doi.org/10.1249/MSS.0b013e31802fa199.
18. Epstein Y, Druyan A, Heled Y. Heat injury prevention--a military perspective. J Strength Cond Res 2012; 26 Suppl 2: S82-86. https://doi.org/10.1519/JSC.0b013e31825cec4a.
19. Nutong R, Mungthin M, Hatthachote P, Ukritchon S, Imjaijit W, Tengtrakulcharoen P, et al. Personal risk factors associated with heat-related illness among new conscripts undergoing basic training in Thailand. PloS One 2018; 13: e0203428. https://doi.org/10.1371/journal.pone.0203428.
20. Jamei M, Nisnevich A, Wetchler E, Sudat S, Liu E. Predicting all-cause risk of 30-day hospital readmission using artificial neural networks. PLOS ONE 2017; 12: e0181173. https://doi.org/10.1371/journal.pone.0181173.
21. Morgan DJ, Bame B, Zimand P, Dooley P, Thom KA, Harris AD, et al. Assessment of machine learning vs standard prediction rules for predicting hospital readmissions. JAMA Netw Open 2019; 2: e190348. https://doi.org/10.1001/jamanetworkopen.2019.0348.
22. Narla A, Kuprel B, Sarin K, Novoa R, Ko J. Automated classification of skin lesions: From pixels to practice. J Invest Dermatol 2018; 138: 2108–10. https://doi.rg/10.1016/j.jid.2018.06.175.
23. Gulshan V, Peng L, Coram M, Stumpe MC, Wu D, Narayanaswamy A, et al. Development and validation of a deep learning algorithm for detection of diabetic retinopathy in retinal fundus photographs. JAMA 2016;3 16: 2402–10. https://doi.org/10.1001/jama.2016.17216.
24. Nelder JA, Wedderburn RWM. Generalized linear models. J R Stat Soc Ser Gen 1972; 135: 370. https://doi.org/10.2307/2344614.
25. Zhang Z. Introduction to machine learning: k-nearest neighbors. Ann Transl Med 2016; 4:218.https://doi.org/10.21037/atm.2016.03.37.

26. Breiman L. Random Forests. Mach Learn 2001; 45: 5–32. https://doi.org/10.1023/A:1010933404324.
27. Chen T, Guestrin C. XGBoost: A Scalable Tree Boosting System. Proc. 22nd ACM SIGKDD Int. Conf. Knowl. Discov. Data Min., San Francisco California USA: ACM; 2016, p. 785–94. https://doi.org/10.1145/2939672.2939785.
28. Zurada JM. Introduction to artificial neural systems. West Publishing Company, Newyork 1992, 1st edition
29. O'Shea K, Nash R. An introduction to convolutional neural networks 2015. Retrieved from arXiv:1511.08458. https://doi.org/10.48550/arXiv.1511.08458.
30. Chawla NV, Bowyer KW, Hall LO, Kegelmeyer WP. SMOTE: Synthetic minority over-sampling technique. J Artif Intell Res 2002;16:321–57.https://doi.org/10.1613/jair.953.
31. Kuhn M. Building predictive models in R using the caret package. J Stat Softw 2008; 28: 1–26. https://doi.org/10.18637/jss.v028.i05.
32. Kalinowski T, Falbel D, Allaire JJ, Chollet F, RStudio, Google T, [ctb Y, cph, Bijl WVD, Studer M, Keydana S, 2023. "Keras: R Interface to 'Keras'.
33. Krittanawong C, Johnson KW, Rosenson RS, Wang Z, Aydar M, Baber U, et al. Deep learning for cardiovascular medicine: a practical primer. Eur Heart J 2019; 40: 2058-73. https://doi.org/10.1093/eurheartj/ehz056.
34. Liaw A, Wiener M. Classification and regression by Random Forest. R News 2002; 2: 18–22.