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Biomedical Applications of Infrared Thermal Imaging: Current State of Machine Learning Classification †

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Abstract: Infrared thermal (IRT) imaging is a modality that allows non-invasive and non-ionizing monitoring of skin surface temperature distribution, providing underlining physiological information on peripheral blood flow, autonomic nervous system, vasoconstriction/vasodilatation, inflammation, transpiration or other processes that can contribute to skin temperature. This imaging method has been used in biomedical applications since 1956 and has proved its usefulness for vascular, neurological and musculoskeletal pathological situations. This research aims to identify and appraise the recent biomedical applications which had used intelligent analysis methods such as machine learning processes to classify and perform decision making towards improving the existing medical care, a literature review is presented and their operation in the biomedical applications of infrared thermal imaging.

Keywords: biomedical applications; classification; infrared thermal imaging; machine learning

1. Introduction

The method of infrared thermal (IRT) imaging allows to record and map large areas of the human body skin surface, it is related with the underlying physiology, namely peripheral blood flow and autonomic nervous system. It can be used as a pathological parameter to adjunct clinical decisions such as diagnosis or treatment evaluations, being easy to use, safe and fast. Since mid 50's it has been employed in clinical practice and research with several applications in the vascular, neurological and musculoskeletal systems [1]. International accepted guidelines [2–4] were developed to standardize the technique and improve its outcomes and massive fever screening standards were produced [5–8].

Over this decade loads of data have been generated, which has been per application individually analyzed and statistical evaluated to produce results, but with technology it is possible to generate information from data, knowledge from information, wisdom from knowledge and make decisions based in this generated wisdom with Artificial Intelligence methods such as machine learning (ML). Examples of this methods that have been employed in other areas and medical imaging modalities are: Artificial Neural Networks (ANN), Support Vector Machine (SVM), Naïve Bayes (NB), k-Nearest Neighbour (k-NN), Fuzzy methods, Decision Trees (DT), Random Forest (RF) and AdaBoost.

It is aim of this research to survey the literature sources such as PubMed, Scopus and Web of Knowledge and identify biomedical applications of IRT imaging with usage of data classification with ML methods.

2. Results of the Literature Survey

The results of the literature survey are presented at table 1, constructed with the year of publication, type of application, ML classifier with better performance, the sample size, the accuracy, sensitivity and specificity.

Sensitivity is related to the test's ability to identify a condition correctly. It is obtained as the number of true positives (TP) divided by the total number of true positives and false negatives (FN) in a population (Equation (1)). Specificity is related to the test's ability to exclude a condition correctly. It is obtained as the number of true negatives (TN) divided by the total number of true negatives and false positives (FP) in a population (Equation (2)). Finally, accuracy is calculated by dividing the total number of successful results by the total population (Equation (3)).

$$Sensitivity = \frac{TP}{TP + FN} \tag{1}$$

$$Specificity = \frac{TN}{TN+FP}, \tag{2}$$

$$Accuracy = \frac{TP+TN}{TP+FP+TN+FN}, \tag{3}$$

Table 1. The IRT imaging biomedical applications with machine learning classification.

Year [Ref.]	Biomedical Application	Best overall Classifier	Sample Size	Accuracy (%)	Sensitivity (%)	Specificity (%)
2002 [9]	Breast cancer	ANN	207 (76 healthy, 98 benign and 33 cancer)	61.94	68.97	80.00
2008 [10]	Breast cancer	ANN	82 (30 asymptomatic, 48 benign and 4 cancer)	80.95	100.00	70.60
2008 [11]	Carpal tunnel syndrome	ANN	56 (26 healthy and 30 pathological)	80.60	-	-
2009 [12]	Carpal tunnel syndrome	ANN	251 (132 healthy and 119 pathological)	72.20 and 80.00 (severe cases)	-	-
2009 [13]	Breast cancer	Fuzzy logic	150 (105 normal and 45 cancer)	80.98	-	-
2012 [14]	Breast cancer	SVM	50 (25 normal and 25 cancerous)	88.10	85.71	90.48
2012 [15]	Breast cancer	SVM	96 (24 normal and 72 cancer)	88.23	-	-
2013 [16]	Breast cancer	Naïve Bayes	98 (21 healthy and 77 cancer)	71.86	-	-
2013 [17]	Breast cancer	AdaBoost	32 (11 healthy, 12 benign and 9 cancer)	83.00	-	-
2013 [18]	Breast cancer	ANN	150 (50 healthy, 50 benign and 50 cancer)	88.76	81.37	90.59
2014 [19]	Dry Eye disease	k-NN	81 (40 responded and 41 not responded)	99.88	99.76	100.00
2014 [20]	Breast cancer	k-NN	40 (26 normal and 14 abnormal)	92.50	-	-
2014 [21]	Breast cancer	SVM	22(16 normal and 6 cancer)	90.91	81.82	100.00
2015 [22]	Back pain	SVM	1000 (300 healthy, 200 faulty posture and 500 lateral spinal curvature)	-	88.00	90.00
2015 [23]	Dry Eye disease	k-NN	104 (21 healthy and 83 affected)	99.80	99.80	99.80
2015 [24]	Breast cancer	k-NN	22 (11 healthy and 11 cancer)	90.91	-	-
2015 [25]	Breast cancer	ANN	240 (160 healthy and 80 cancer)	92.89	-	-
2015 [26]	Breast cancer	SVM	80 (50 healthy and 30 with findings)	91.25	93.30	90.00
2015 [27]	Diabetic foot	ANN	60 (30 diabetic and 30 non-diabetic)	94.33	97.33	91.33

2016 [28]	Finger skin injury	k-NN	75 (50 normal and 25 affected)	100.00	-	-
2016 [29]	Facial nerve function	RBFNN	390 (unilateral)	94.10	-	-
2016 [30]	Breast cancer	fuzzy active contours	60 patients	91.89	85.00	-
2016 [31]	Breast cancer	Fuzzy C Means	670 images from 67 patients	88.10	85.71	90.48
2016 [32]	Breast cancer	Decision Tree	50 (25 normal and 25 cancer)	98.00	96.66	100.00
2016 [33]	Thyroid abnormalities	Decision Tree	51 (21 normal and 30 abnormal-hyper and hypo)	95.00	96.00	92.00
2017 [34]	Drunkenness state	ANN	41 (28 drunk and 13 sober)	86.00	-	-
2017 [35]	Breast cancer	SVM	80 (40 normal and 40 abnormal)	90.00	87.50	92.50
2017 [36]	Exercise-induced fatigue	ANN+SVM	5700 images from 19 subjects	81.51	-	-
2017 [37]	Breast cancer	SVM	244 (100 normal, 66 benign and 78 cancer)	94.87	-	-
2017 [38]	Breath analysis	ANN	25 experiments by 1 subject	100.00	-	-
2017 [39]	Diabetic foot	k-NN	117 (51 healthy, 33 with and 33 without neuropathy)	93.16	90.91	98.04
2018 [40]	Rheumatoid arthritis	k-NN	60 (30 controls and 30 patients)	83.00	86.60	79.00
2018 [41]	Breast cancer	ANN	725 (219 healthy, 371 benign lesions and 235 cancer)	73.38	78.00	88.00
2018 [42]	Hypertension	ANN	300 (150 healthy and 150 patients)	89.00	85.70	92.90
2018 [43]	Expression recognition	ANN	3561 from 22 subjects (2124 positive and 1437 negative)	85.54	-	-
2018 [44]	Breast cancer	SVM	120 (70 abnormal and 50 normal)	98.00	98.00	98.00
2018 [45]	Burn wounds	Random forest	34 patients	85.35	-	-
2018 [46]	Diabetic foot	k-NN	117 (51 health, 33 diabetics without neuropathy and 33 with)	93.16	90.91	98.04
2018 [47]	Diabetes	Random forest	338 (180 diabetic and 158 non diabetic)	89.63	96.87	98.80
2018 [48]	Skin cancer	k-NN	85	60.00	-	-
2018 [49]	Diabetic foot	k-NN	54	92.50	-	-
2019 [50]	Breast cancer	SVM	60 (25 healthy, 23 benign and 12 malignant)	83.22	85.56	73.23
2019 [51]	Diabetic foot	ANN	246 (150 Diabetic without complications, 36 with complications and 60 healthy)	91.00	-	-
2019 [52]	Cardiovascular disease	Naïve Bayes	150 (80 non-CVD and 70 CVD)	90.00	80.00	90.00
2019 [53]	Hemodynamic Shock	Random forest	539 (253 continuous intra-arterial blood pressure)	73.00	65.00	82.00
2019 [54]	Stress recognition	ANN	93 sets of data from 17 (9 males and 8 females)	78.33	-	-
2019 [55]	Skin cancer	SVM	320 (185 malignant and 135 benign)	61.00	87.00	11.00
2019 [56]	Skin cancer	SVM	46 (16 melanomas and 30 melanocytic nevi) cooling	84.20	91.30	11.00
2019 [57]	Diabetic foot	k-NN	39 (15 with DFU ischemic or infected)	81.25	80.00	100.00

3. Discussion and Conclusions

Based on the survey, the biomedical applications of IRT imaging using ML classification were: breast cancer detection (21), Diabetic foot disease (6), Skin cancer (3), Carpal Tunnel Syndrome (2), Dry eye disease (2), Back pain, Finger skin injury, Facial nerve function, Thyroid abnormalities, Drunkenness state, Exercise-induced fatigue, Breath analysis, Rheumatoid arthritis, Hypertension, Expression recognition, Burn wounds, Diabetes, Cardiovascular disease, Hemodynamic Shock and Stress recognition.

A comparison of the ML classifiers performance in the biomedical applications is outside of the scope of this survey, since the datasets are different, and it will be addressed in a further publication.

The used ML classifiers in biomedical applications of IRT imaging were ANN (15), k-NN (12), SVM (10), Fuzzy methods (3), RF (3), DT (2), NB (2), AdaBoost and ANN+SVM (1).

The highest accuracy reported, 100%, was using ANN in Breath analysis [38] and k-NN in Finger skin injury [28], the overall assessment parameters better classification was obtained using k-NN in Dry eye disease [23].

Despite the major biomedical application of IRT imaging data with ML classifier being in Breast cancer detection, this application has been not recommended as primary screen method [58].

There is no doubt about the utility and usefulness of data classifiers in biomedical application of IRT imaging, which is still unexplored in many proved applications. This is due to certain barriers, such as the lack of familiarity of the principles and the imaging technique by the health professionals, and the lack of a standard imaging file format, which makes data exchange and integration into information systems and development of advanced Computer Aided Diagnosis tools difficult.

Examples of applications that could have great success in using intelligent data classifiers relate to Raynaud's phenomenon, soft tissues rheumatism, blood pressure, hand-arm vibration syndrome, peripheral nerves compressions, complex regional pain syndrome, fever screening, dermatological disorders, temporomandibular joint conditions, renal dialysis, chemotherapy assessment and rehabilitation medicine procedures assessment. Larger data samples are also required for better overall results.

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