Menemukan *Novelty* Penelitian

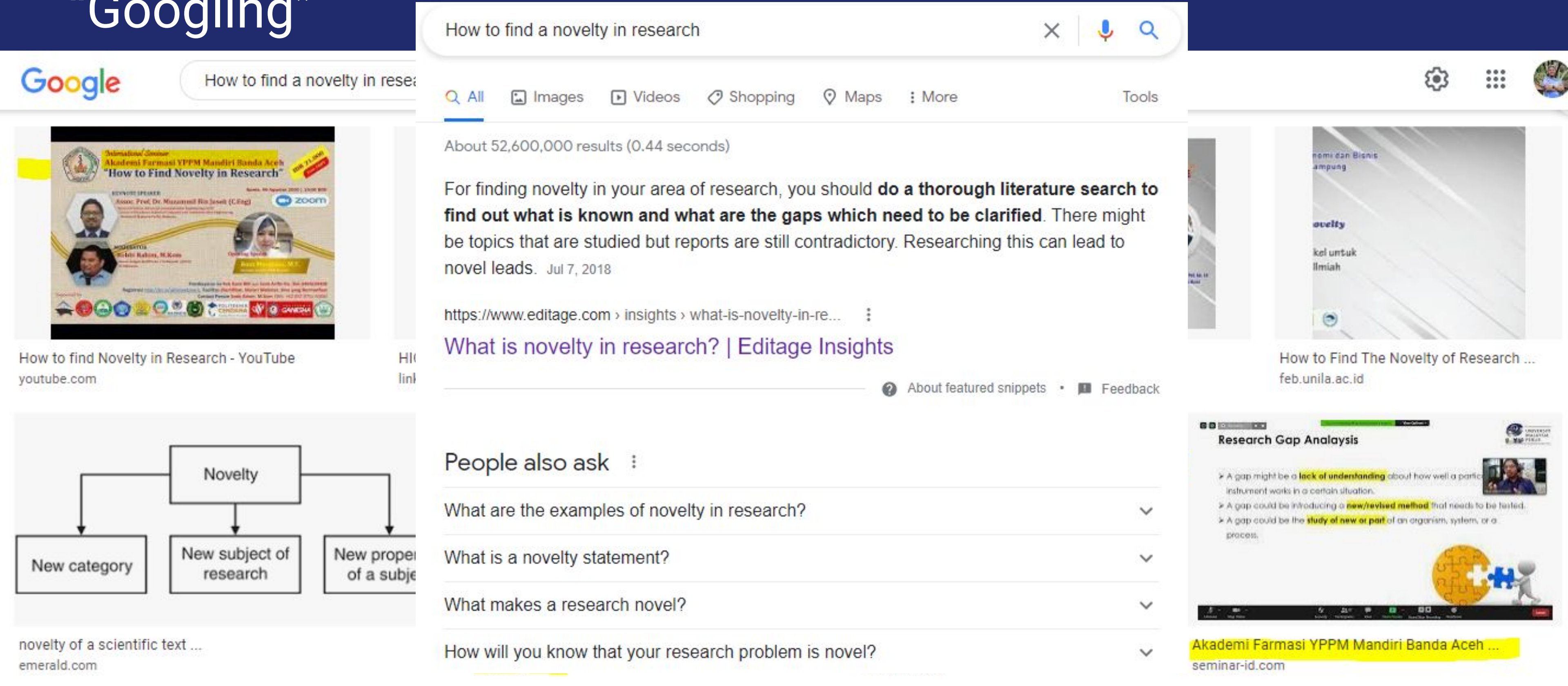
Agung W. Setiawan

Kamis, 23 Juni 2022

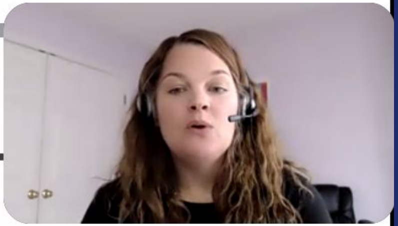
Bagaimana cara mencari kebaruan riset?

Bagaimana cara mencari kebaruan riset?

"Googling"



Invited Speech Lisa Bosman Purdue University, West Lafayette, IN, USA



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DRAFTING MANUSCRIPT – RULES OF T

Introduction

- Part 1: What is the problem?
- Part 2: What are current solutions to the problem?
- Part 3: What gaps remain?
- Part 4: What is the proposed solution (e.g., your intervention and research question)?

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Vision-Based Gait Recognition: A Survey

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Corresponding author: Uday Pratap Singh (usinghiitg@gmail.com)

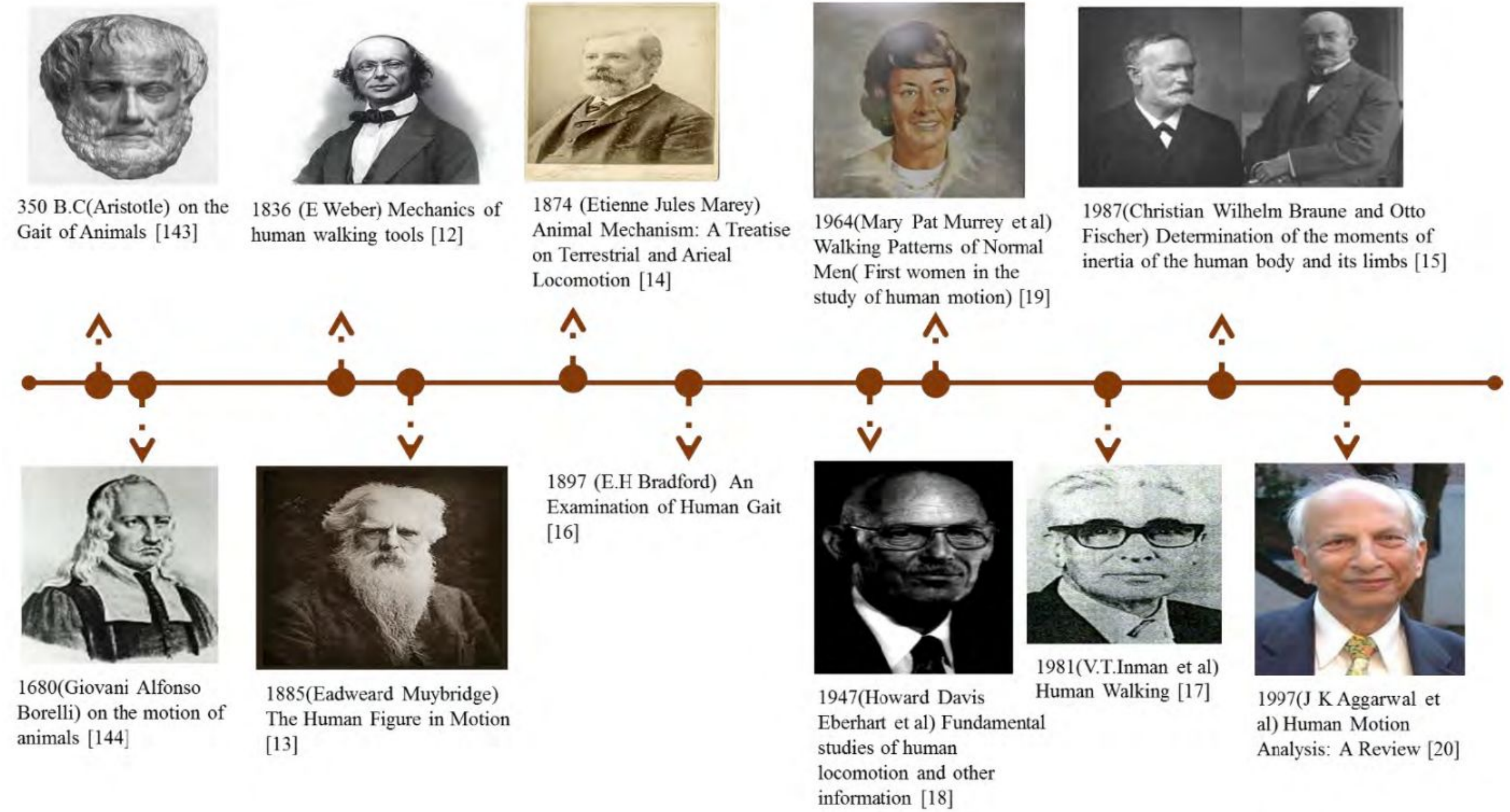

FIGURE 3. Summarized the contribution of key authors in the history of human motion analysis. Some images in this figure and others are taken from the internet, and URLs are provided in appendix.

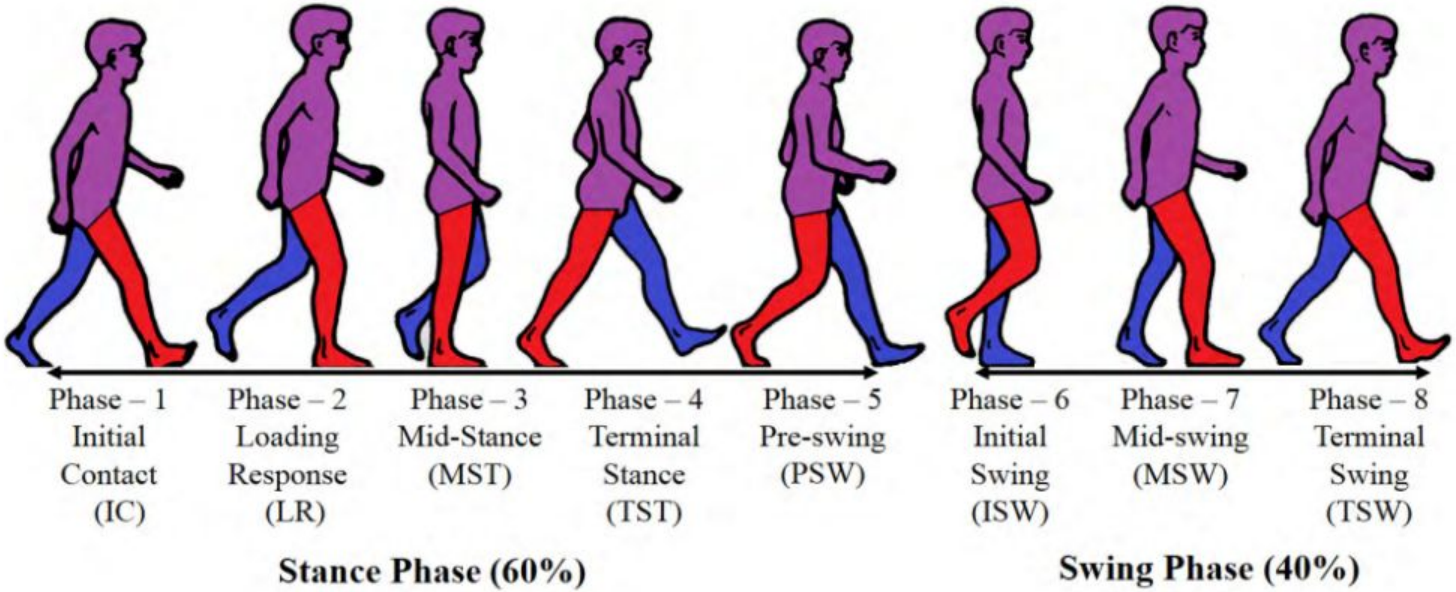

FIGURE 4. Phases of the gait cycle, right leg (red color) considered as a reference leg [10].

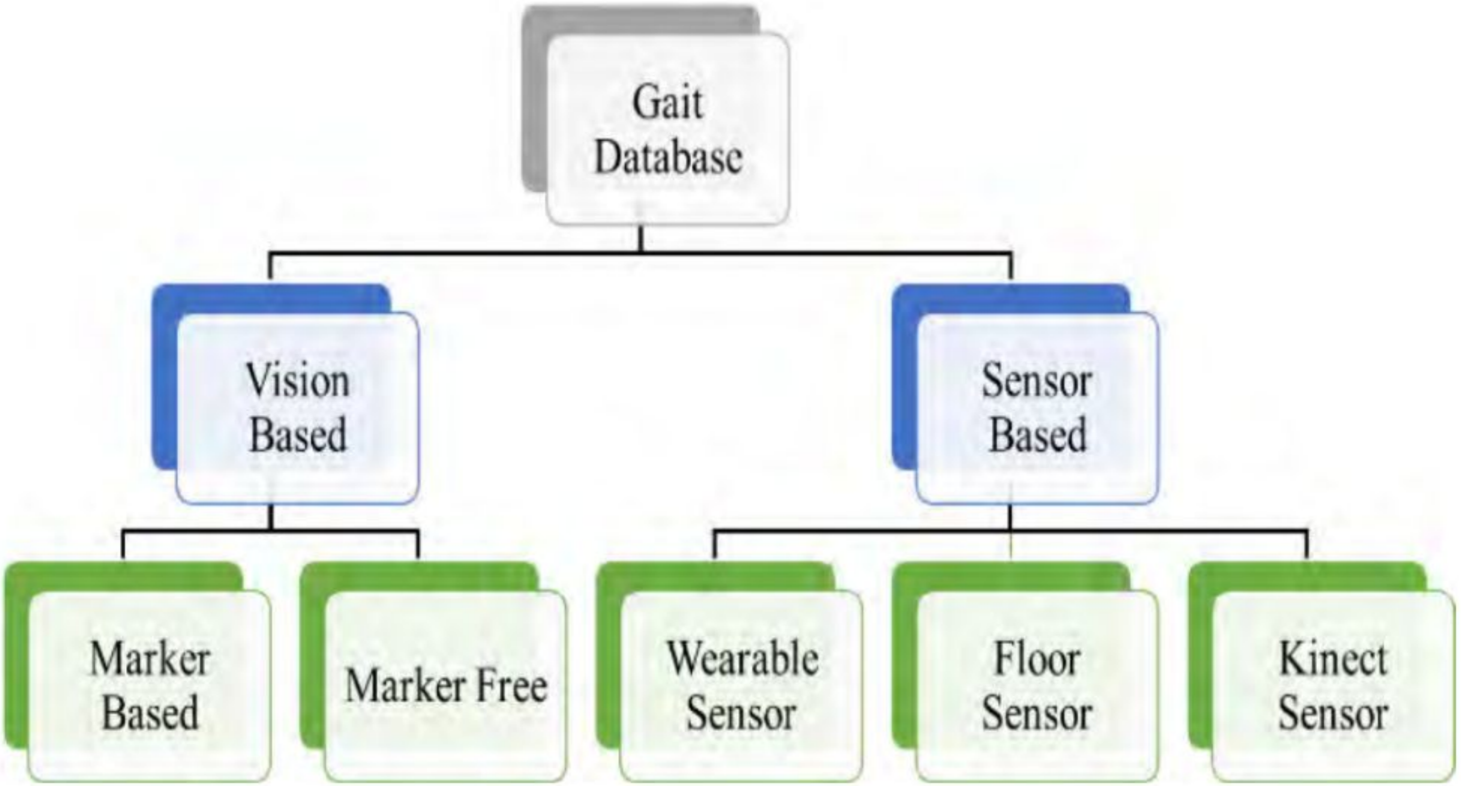

FIGURE 10. Suggested taxonomy of gait dataset.

TABLE 3. Shows year wise creation of vision based dataset. Acronym of words used in table: model-free(MF), model-based(MB), indoor(I), outdoor(O), floor(F), treadmill(T), concrete(C), ground(G).

S. No.	Dataset	Ref./year	No. of Subjects	No. of Seq.	Gender Ratio (M/F)	Covariate Conditions	Env.	Surf.	Frame Rate /Size	Resource	MF	MB
1	Kyushu University, KY4D Database-B: Curve Walk	Iwashita et al. [53] / 2014	42	168	-	3 view directions : frontal view(~ 0^o), side view(~ 45^o) and side view(~90^o)	I	F	-	16 cameras	✓	
2	Kyushu University, KY4D Shadow Database	Iwashita et al. [54] / 2014	54	324	-	Carrying bag, cloth variations	I	F	-	2 infrared light, 1 camera	✓	
3	OUISIR Speed Transition (GaitST)	Lu et al. [44] / 2014	179	-	-	Speed transition, acceleration speed (1km/h to 5km/h),deceleration speed (5km/h to 1km/h)	I	F,T	60fps / -	1 camera	✓	
4	Cleveland State University, Human Motion & Control Lab	Moore et al. [65] / 2014	15	-	11/4	5 walking variations	I	T	-	10 osprey cameras, 47 markers		✓
5	Korea Institute of Science & Technology , KIST	Yun et al. [64] / 2013	113	-	50 / 63	8 multiview variations with constant speed (3km/h)	I	T	- / -	8 cameras, 15 markers		✓
6	OUISIR Large Population (OULP)	Iwama et al. [40] / 2013	4007	-	2135 / 1872	-	I	F	30fps / 640x480	2 cameras	✓	
7	University of Cordoba, AVA-Multiview	Fernandez et al. [55] / 2013	20	1200	16 / 4	Multiview conditions	I	F	25fps / 640x480	6 cameras	✓	
8	Indonesian Gait Database	Mahyuddin et al. [57] / 2012	212	-	102 / 110	5 conditions: view variations, carrying condition, surface, shoe type and time	I	F	90fps / -	LED markers, 1 video camera		✓

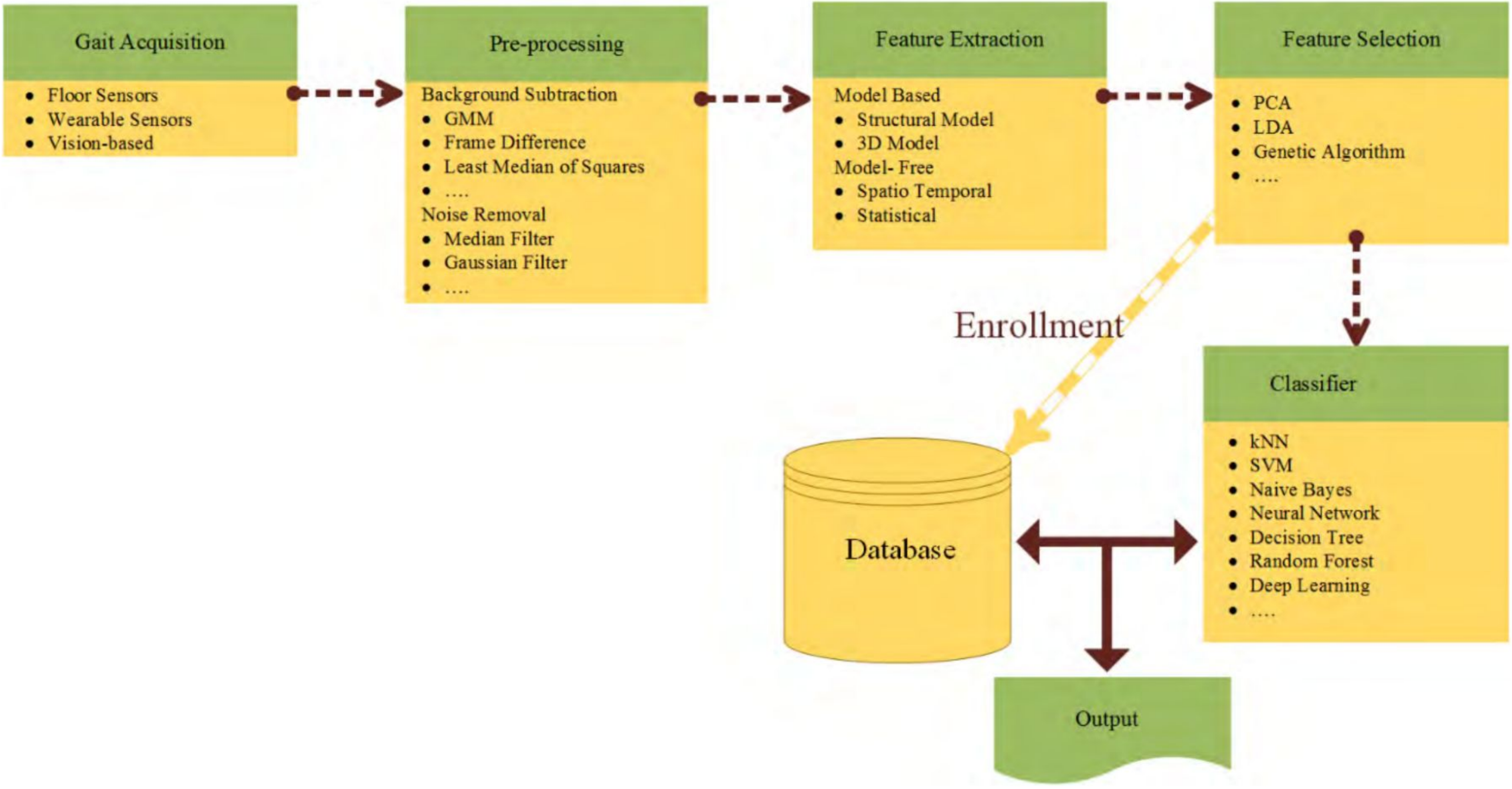

FIGURE 5. Generalized gait based recognition.

TABLE 2. Overview of the most adopted classifier in gait recognition.

Classifier	Studies	Benefits
kNN	[33][96][113][125][115][32] [126] [127][97][124] [103][37] [121][122]	Simple and efficient in computation, if training dataset is large
Navie Bayes	[33][97][129][120]	Very simple and easy to implement and fast because required less training data and make probabilistic predictions
SVM	[125][104][124][84]	Use kernels with the absence of local minima and achieve sparseness to the solution and capacity control achieved by optimizing the margins.
DCNN	[118]	Achieves high accuracy in recognition, but required good GPU for training and need many training data.

TABLE 5. Model-based approaches based on approaches for gait recognition with accuracy rate.

S. No.	Reference/ Year	Technique/ Approach	Gait Parameters/ Features	Dataset	Evaluation / Classifier	Accuracy(%)
1	Bobick et al. [67] / 2001	Parametric Method	Static body parameters. Stride parameters.	Recorded 18subjects gait data in open indoor. Two view angle: 45, frontal parallel. Recorded 15 out of 18 in outdoor with shadow.	kNN	Height + stride : 49% Single stride : 21%
2	Abdelkader et al. [66] / 2002	Parametric Method	Height and stride parameters.	Created 45 subjects gait data: 7 females , 28 males	-	-
3	Yoo et al. [71] / 2008	2D Stick Figure	Trajectories based kinematic characteristics(Linear and angular position, displacement and time derivation).	Southampton HID database, 100 subjects	BPNN	Training vector:150 Testing vector: 30 CCR : 90% , Good Training vector:150 Testing vector : 30, CCR: 83.3% , Fair Training vector:150 Testing vector : 30 CCR: 83.3% , Bad
4	Yoo et al. [72] / 2011	2D Stick Figure	Motion parameters(cycle time and gait speed).	-	k-NN	Subject: 30 k=1:96.7% , k=3:93.3% k=5:96.7% Subject:60 k=1:91.7% , k=3:86.7% k=5 : 85.7% Subject: 100 k=1:84.0% , k=3:80.0%, k=5:82.0%
5	Wagg et al. [73] / 2004	Hierarchical shape	Joint rotations(hip, knee,and ankle). Static parameters. Total 45 parameters.	HID database : 115 subjects	NN+ ANOVA	Indoor : ≈ 84% Outdoor : ≈ 64%
6	Bouchrika et al. [74] / 2014	Haar Template Matching	Gait kinematic features.	CASIA Dataset- B	k-NN	73.60%

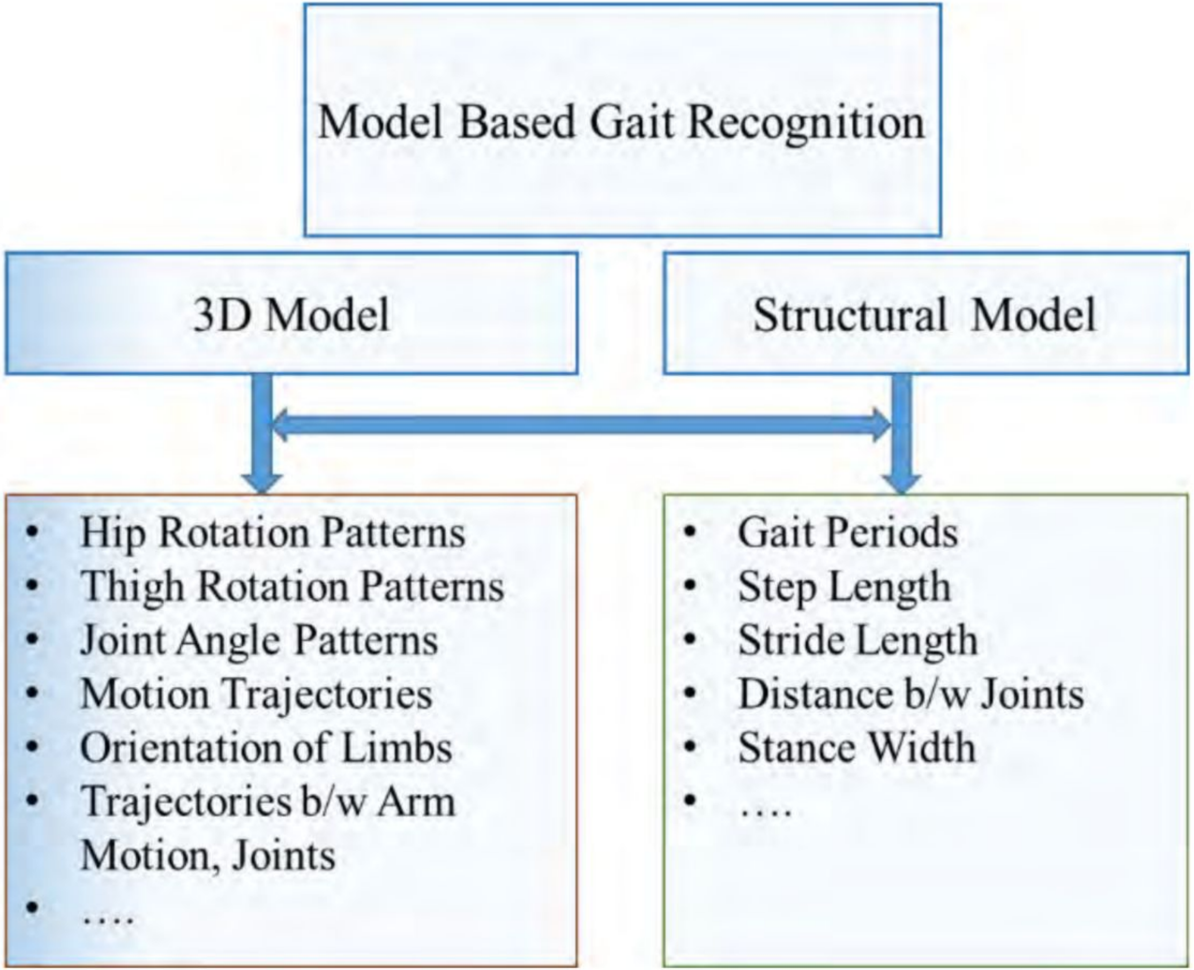

FIGURE 12. **Model based gait recognition approaches and possible features that can be used to represent a gait signature.**

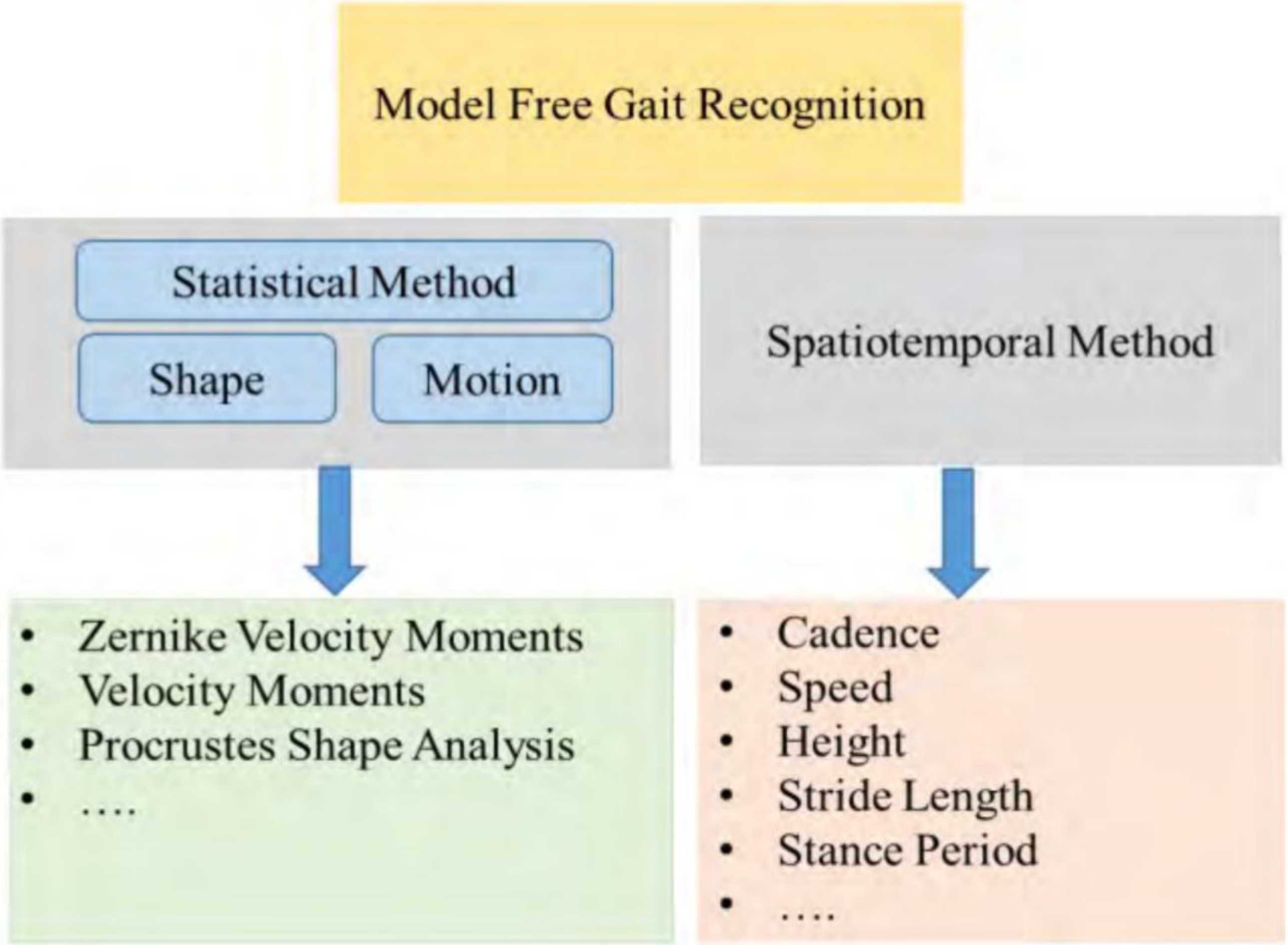

FIGURE 15. **Model-free approaches and their corresponding features.**

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Latest Research Trends in Gait Analysis Using Wearable Sensors and Machine Learning: A Systematic Review

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TABLE 4. Gait parameters and applications.

Gait Parameter	Medical	Fitness	Security
Body Posture	✓	✓	✓
Covered Distance	✓	✓	
Fall	✓	✓	
Gait Phases	✓	✓	✓
Joint Angle	✓	✓	
Momentum	✓	✓	
Muscle Force	✓	✓	
Stance Time	✓		
Step Angle	✓	✓	✓
Step Length	✓	✓	✓
Step Time	✓		
Step Width	✓	✓	✓
Stride Length	✓	✓	✓
Stride Velocity	✓	✓	✓
Swing Time	✓		
Rhythm	✓	✓	✓

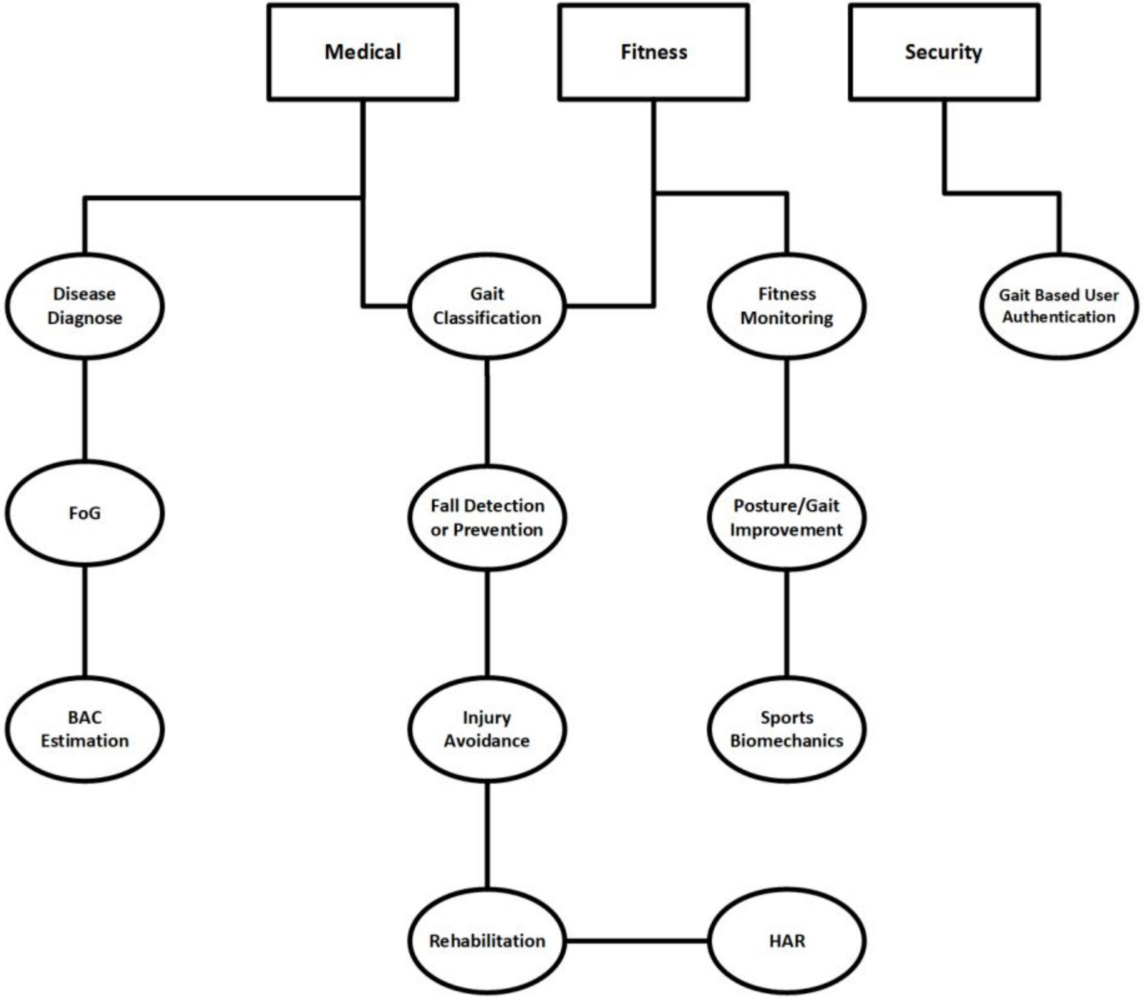

FIGURE 3. Common applications of gait analysis.

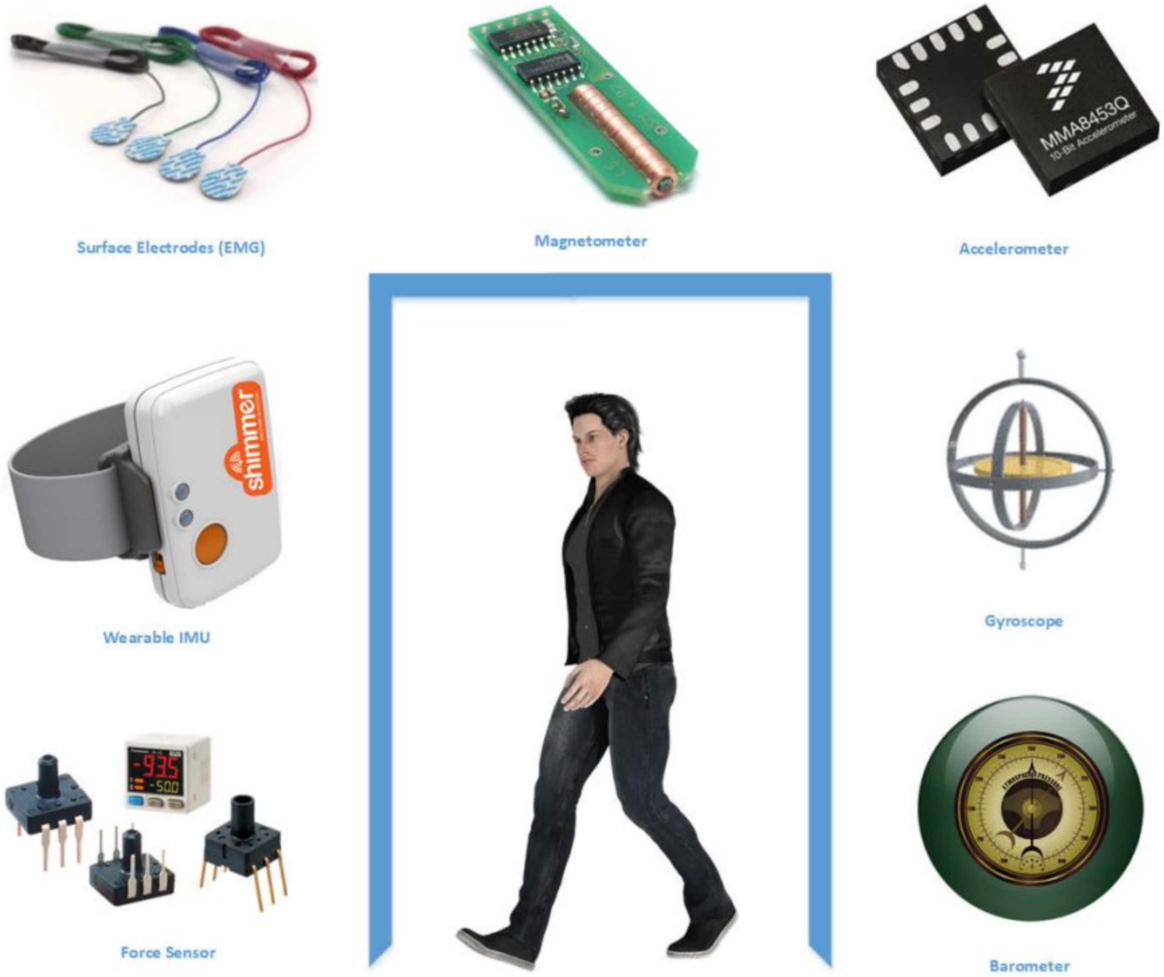

FIGURE 4. **Examples of wearable sensors for gait analysis.**

Sensors **2015**, *15*, 22089-22127; doi:10.3390/s150922089

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Review

Inertial Sensor-Based Gait Recognition: A Review

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Academic Editor: Vittorio M. N. Passaro

Received: 21 July 2015 / Accepted: 22 August 2015 / Published: 2 September 2015

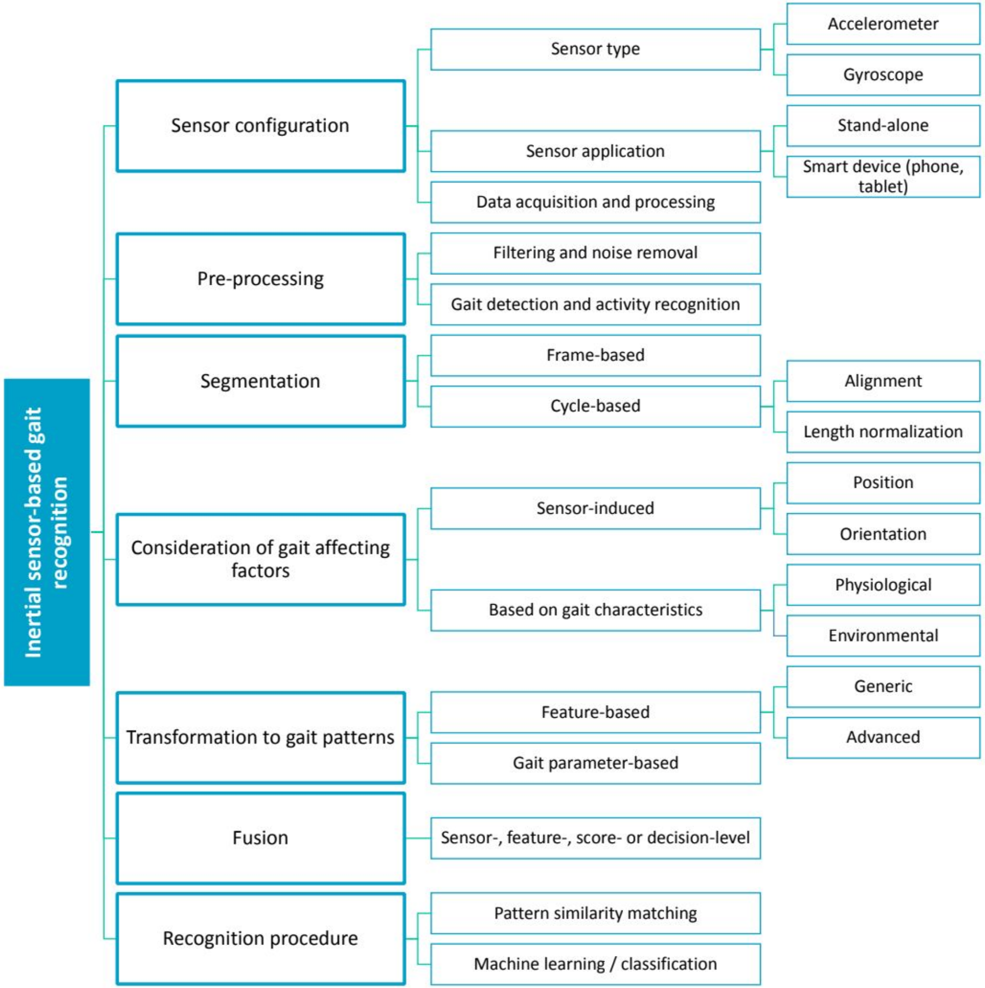
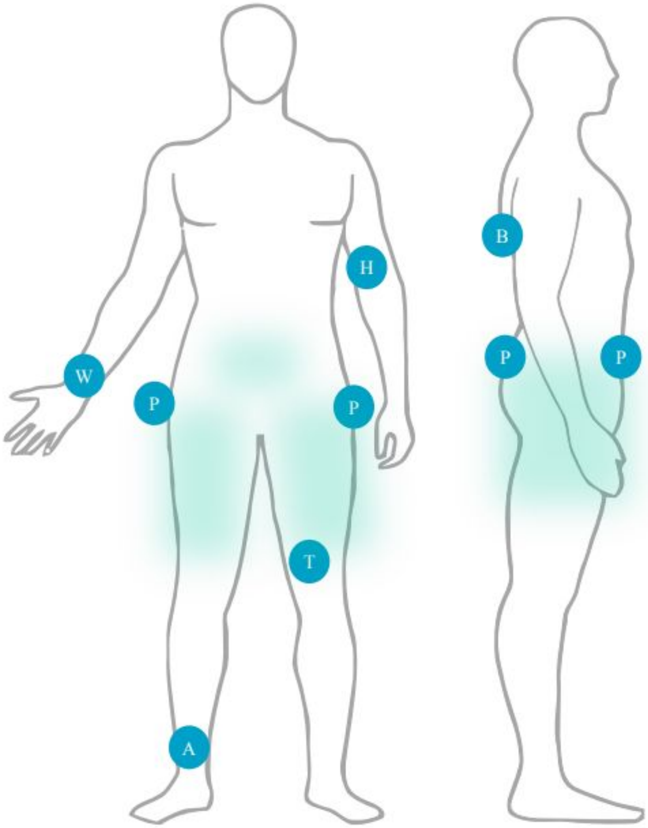


Figure 2. Methodological layout of existing inertial sensor-based gait recognition approaches.



Position	Sensor type m_a (measurand m, number of axes a)			
	$a_3\omega_3$	a_3	ω_3	a_2
B Back	[27][a]	[27][a], [28][b]	[42][b]	[48][a]
H Arm		[29][bc]		
W Wrist		[29][d]		
P Pelvis	[27][c,d]	[51][c], [29,50][d], [52][c,d,e]		
T Thigh		[29][c]		
A Ankle		[29,43][df]		
Pocket	[53][c,d]	[44,49,52,54][c,d]		

[a] Center
[b] Upper
[c] Left
[d] Right
[e] Front
[f] Lower

Figure 3. Sensor positions.

POT9-14 IBEC 2014 Jointly with uHealthcare 2014

Design and Implementation of Mobile Cataract Detection using Statistical Texture Analysis

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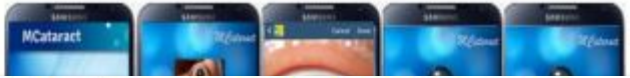
Abstract—**The increasing number of cataracts in developing country, especially in Indonesia will be a serious public health problem as a leading cause of blindness if there is a delay in handling cataracts. In this paper, we discuss about implementation of mobile cataract statistical texture analysis. The st analysis is proposed as a feature ex and k-NN (k-Nearest Neighbor) as method. The result of the syst percentage value of True Positiv percentage value of False Positive is**

A. Eye Image



Mobile cataract detection using optimal combination of statistical texture analysis 22 2015
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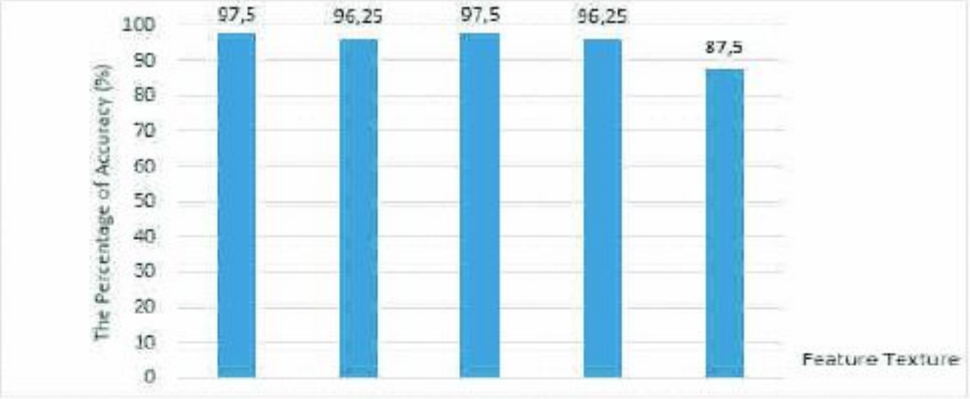
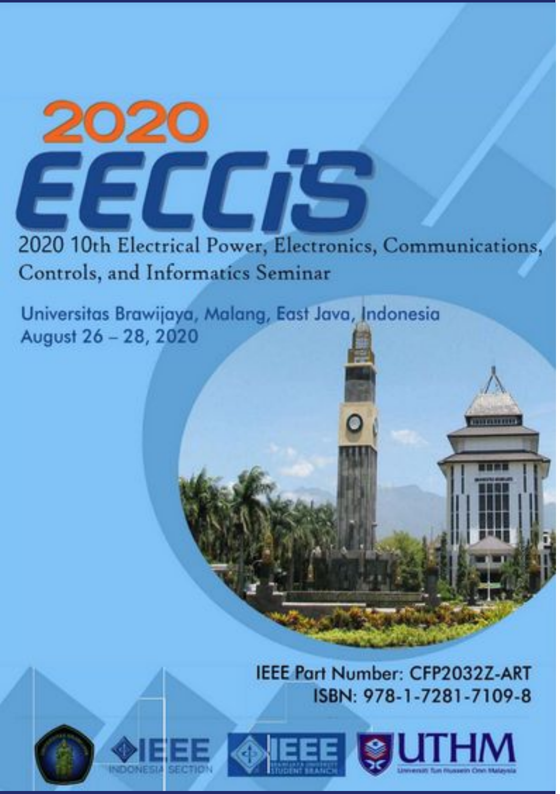


Uniformity	✓	✓	✓	✓	✓
Contrast	✓		✓		
Dissimilarity	✓	✓	✓		
Correlation	✓	✓		✓	
Homogeneity	✓	✓			



Development of Research-based Learning in Introduction to Biomedical Engineering Course for Undergraduate Electrical Engineering Students

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***Abstract*—Research-based learning (RbL) is introduced in the 2019/2020 academic year to increase the students' attendance and engagement. Furthermore, the proposed learning approach is used to prepare the students for admitting and successfully completing the graduate study. Around 80%, 12 weeks, of the course allocation, is allocated to implement the RbL. In the mentoring session, the instructor act like a coach that guides the students to conduct the research step-by-step and ensure they use proper research methodology. The study has shown that the students become more active in the learning process and increase the students' engagement. Other students show that the RbL not only can be used to solve the research problem(s) but also motivate them to think creatively. One of the main roles of the instructor is to guide and ensure the students do their works comply with the proper research methodology. The implementation of RbL not only improving students' final scores but also gives the students an opportunity to work in the research environment through learning research methodology.**

education [4], improving students' learning experience [5] and engagement [6].

Furthermore, the implementation of RbL in undergraduate students not only improve their knowledge but also research skill [7] and attitude to complete their research competencies [2]. The RbL can increase significant student's gain in the skills [8], such as data interpretation; manipulation; and analysis [9]. Moreover, introducing RbL in the undergraduate programs can be used to develop soft skills, such as self-efficacy [10]; students' autonomy; leadership; communication, teamwork; creativity, and decision making [11].

The aim of implementing RbL in this course is to address one of the program's educational objectives of the study program, i.e. "Our graduates are capable to be admitted in and successfully completing their graduate studies." RbL can be used to encourage the students to apply postgraduate study [4],

Contoh pekerjaan mhs EL5114

Kajian Literatur tentang Pengolahan Citra Medis untuk Klasifikasi Covid-19

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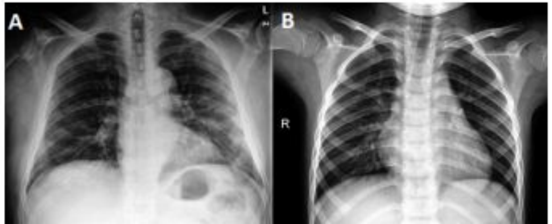
***Abstract*—Penyakit coronavirus (Covid-19) adalah kumpulan virus yang menginfeksi sistem pernapasan dan menular melalui respirasi droplet atau kontak berdekatan dengan orang yang telah terkontaminasi virus Covid-19. Berdasarkan data yang diperoleh dari World Health Organization (WHO) hingga bulan Oktober 2020 ini, telah 37,423,660 jiwa telah dikonfirmasi terkena virus Covid-19 dengan 1,074,817 jiwa diantaranya meninggal dunia. Pendeteksian Covid-19 yang paling banyak digunakan adalah Polymerase Chain Reaction (PCR). Selain itu, juga dapat dilakukan dengan Medical Imaging seperti CT-Scan, X-Ray, Ultrasound, dan lain-lain. Kelebihan PCR dibandingkan Medical Imaging ialah tingkat akurasi yang lebih tinggi namun untuk kemungkinan terkontaminasi lebih besar. Namun Medical Imaging memberikan hasil yang subjektif. Oleh karena itu, Artificial Intelligence menggunakan Deep Learning dapat digunakan untuk mendeteksi Covid-19 dan mengklasifikasikan hasil citra medis sesuai dengan karakteristik data yang diolah. Oleh karena itu, studi pustaka ini bertujuan untuk membahas dan mengkaji lebih dalam metode yang paling efektif untuk mengklasifikasi citra hasil medis. Dataset yang digunakan berupa dataset jenis publik dan dataset privat. Dataset ini akan dibagi menjadi beberapa bagian diantaranya Training Data, Validation Data dan Testing data. Dataset yang digunakan akan dibagi menjadi 2 kelas yaitu Covid-19 dan NonCovid-19. Selanjutnya dilakukan**

kepala dan diare. Hingga saat ini belum ada vaksin yang tersedia untuk pencegahan Covid-19. Karena itu masyarakat bisa dengan mudah terinfeksi virus tersebut [2].

Berdasarkan data yang diperoleh dari *World Health Organization* (WHO) hingga bulan Oktober 2020 ini, sebanyak 37,423,660 jiwa telah dikonfirmasi terinfeksi virus Covid-19 dan 1,074,817 jiwa diantaranya meninggal dunia. Angka yang dicapai ini cukup besar sehingga menyebabkan beberapa negara di dunia menerapkan protokol kesehatan, salah satunya adalah peraturan *lockdown*.



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The Accuracy

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HASIL AKURASI KLASIFIKASI COVID-19 PADA CITRA CT-SCAN BERDASARKAN VARIASI METODE PRA-PENGOLAHAN CITRA

Information		A	B	C	D	E	F	G	H	I	J	K	L
Resize	Deform	✓	✓	✓	✓	✓			✓		✓		
	Non-Deform						✓	✓		✓		✓	✓
Enhancement	Original	✓	✓				✓						
	EFF			✓						✓	✓	✓	
	CLAHE				✓			✓	✓				✓
	HE					✓							
Normalization	[-1 1]	✓		✓	✓	✓	✓					✓	✓
	[0 1]		✓					✓	✓	✓	✓		
Validation Accuration	Initial	50.25%	52.98%	51.50%	53.28%	42.98%	48.38%	56.50%	51.58%	57.36%	55.25%	51.37%	48.80%
	Transfer Learning	58.75%	63%	65%	66.42%	58.11%	64.09%	83.75%	63.26%	63.09%	66.75%	67.83%	59.00%
	Fine Tuning	88%	87.50%	85.50%	84.67%	85.09%	85.04%	87.75%	86.62%	78.80%	82.50%	78.80%	82.25%
Test Accuration		82.29%	84.38%	85.42%	88.54%	79.17%	82.29%	83.33%	88.54%	80.21%	81.25%	72.92%	82.29%

TABLE II
PERBANDINGAN VARIASI METODE RESIZE DEFORM DAN NON-DEFORM

Experiment	Dependent Variable		Best Result	Difference
	Enhancement	Norm Range		
A & F	original	[-1 1]	equal	0%
C & K	EFF	[-1 1]	Deform	12.50%
I & J	EFF	[0 1]	Deform	1.04%
D & L	CLAHE	[-1 1]	Deform	6.25%
G & H	CLAHE	[0 1]	Deform	5.21%

TABLE III
PERBANDINGAN VARIASI METODE ENHANCEMENT ORIGINAL, EFF, CLAHE, DAN HE

Experiment	Dependent Variable		Best Result	Difference
	Resize	Norm Range		
A, C, D, E	Deform	[-1 1]	CLAHE	3.12%
H & I	Deform	[0 1]	CLAHE	8.33%
K & L	non-Deform	[-1 1]	CLAHE	9.37%
G & I	non-Deform	[0 1]	CLAHE	3.12%

TABLE V
PERBANDINGAN HASIL DENGAN PENELITIAN LAINNYA

No	References	Number of images	Accuracy
1	[33]	746	86,50%
2	[34]	1485	84%
3	[25]	757	approx. 84%
4	[10]	4257	87,12%
5	[35]	1020	83,33%
6	Our optimum result	2479	88,54%

menggunakan rentang normalitas [0 1]. Sedangkan untuk metode enhancement EFF cenderung tinggi pada akurasi yang menggunakan rentang normalisasi [-1 1]. Secara keseluruhan, metode normalisasi [0 1] lebih unggul dibandingkan dengan [-1 1].

Hal ini dapat dianalais dari hasil histogram original, CLAHE dan EFF. Untuk histogram original dan CLAHE, citra belum mengalami proses normalisasi. Sehingga hasil dengan penam-

Effect of CT-Scan Image Resizing, Enhancement and Normalization on Accuracy of Covid-19 Detection

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***Abstract*—Covid-19 continues to be a global health problem with an impact on at least 70 million people exposed and more than 1.5 thousand people died in December 2020. Detection by RT-PCR as the gold standard of WHO is still difficult to reach in some areas and has a low sensitivity issue. Many studies have focused on the detection of Covid-19 using computer vision, especially deep learning methods. However, it is necessary to evaluate the preprocessing stage before carrying out the classification to increase the accuracy of its detection. Therefore, the objective of this study was to compare the choice of the CT-Scan image pre-processing method and its effect on the results of covid-19 classification accuracy. The benefit of this study is that it can be used as a recommendation when considering the choice of**

speed of detection of
the accuracy and fast
virus propagation im
The WHO has establ
the detection of Covi
world, for example in
PCR units and the lab
limited. This is also
Furthermore, RT-PCI
and low sensitivity
looking for other alter

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CERTIFICATE
No : B/31162/IT2.IX.5.1.1/DL.07.00/2021
This is to certify that
Nurdina Gita Pratiwi
Gets a
Student Paper Award
In conjunction with the 2021 International Seminar on Intelligent Technology and Its Applications
"Intelligent Systems For The New Normal Era"
Held by Sepuluh Nopember Institute Of Technology (ITS)
on 21-22 July 2021

Virtual Conference

Head of Electrical Engineering Department	ISITIA 2021 General Chairman
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Author(s)	Year			Methods	Cancer	Metric(s)
Awan et al.	2019	DL	DenseNet	DenseNet	Qatar University's Instituti	Accuracy: 81.9
Awan et al.	2019	DL	GoogleNet	Colour normalization, U-Net and G	Qatar University's Instituti	Accuracy: 85
Awan et al.	2019	DL	ResNet	ResNet50	Qatar University's Instituti	Accuracy: 84.00%
Dabass et al.	2019	DL	CNN	31-layer CNN (DL)	not specified	Accuracy: 96.97
H. Yoon, et al.	2019	DL	VGG modified	modified VGG	Center for Colorectal Can	Accuracy: 82%
J. Malik, et al.	2019	DL	CNN	adaptive CNN	Qatar University's Instituti	Accuracy: 94.5%
Sena et al.	2019	DL	CNN	12-layer CNN (DL)	Modena University Hospit	Accuracy: 93.28
Tavolara et al.	2019	DL	GAN	conditional generative adversarial	Private dataset	F1-score: 94.02
Tavolara et al.	2019	DL	GAN	conditional generative adversarial	Private dataset	F1-score: 95
Abbas, et al.,	2020	DL	AlexNet	Alex-Net	LC25000,	Accuracy: 97.26%
Abbas, et al.,	2020	DL	ResNet	ResNet-18	LC25000,	Accuracy: 98.80%
Abbas, et al.,	2020	DL	ResNet	ResNet-34	LC25000,	Accuracy: 99.18%
Abbas, et al.,	2020	DL	ResNet	ResNet-50	LC25000,	Accuracy: 99.60%
Abbas, et al.,	2020	DL	ResNet	ResNet-101	LC25000,	Accuracy: 99.80%
Abbas, et al.,	2020	DL	VGG	VGG-19	LC25000,	Accuracy: 98.93%
Bukhari et al. [9]	2020	DL	ResNet	ResNet-18	LC25000,	Accuracy: 93.91%
Bukhari et al. [9]	2020	DL	ResNet	ResNet-30	LC25000,	Accuracy: 93.04%
Bukhari et al. [9]	2020	DL	ResNet	ResNet50.	LC25000,	Accuracy: 93.04%
H.-G. Nguyen, et al.	2020	DL	CNN+CapsNet	combination of classical CNN and	Tissue Bank Bern (Institut	Accuracy: 95.3%
Hatuwal and Thapa	2020	DL	CNN	Convolution Neural Network (CNN	Lung LC25000	Accuracy: 97.2%.
Liang et al.	2020	DL	CNN MFF	multi-scale feature fusion convoluti	National Cancer Center of	Accuracy: 96%
N. Dif and Z. Elberrich	2020	DL	ResNet	ResNet-121		Accuracy: 94.52%
Qasim et al.	2020	DL	CNN	CNN	Colon	Accuracy: 99.6%
A.B. Hamida, et al.	2021	DL	ResNet	ResNet	CRC-5000, NCT-CRC-HE	Accuracy: 99.98%

Decision Tree (DT), RF, Gradient Tree Boosting, SVM, k-Nearest Neighbor (k-NN), perceptron and logistic regression are used and give the best accuracy of 99.43% that achieved using Gradient Tree Bosting Nishio, Nishio, Jimbo and Nakane (2021).

Colon cancer detection has accuracies of 92.83% and 96.16% are achieved using multiclass features and Deep Neural Network (DNN) on Colorectal Histology and NCT-CRC-HE-100K dataset Ghosh, Bandyopadhyay, Sahay, Ghosh, Kundu and Santosh (2021). The combination of feature aggregation and multiple-instance learning approach gives an accuracy of 90.19%.

compact CNN based architecture that can be trained from scratch even on scarce and low-resolution data. deep CNNs with transfer learning achieved a superior cancer identification. CNN-based methods provide an average detection sensitivity of 94.5% which is about 5% more than the best performing traditional method. Malik, Kiranyaz, Kunhoth, Ince, Al-Maadeed, Hamila and Gabbouj (2019)

cancer classification via 31 layers deep CNN. The proposed model results classification accuracy of 96.97% for two-class grading and 93.24% for five-class cancer grading. Dabass, Vig and Vashisth (2019)

VGG E, which had an accuracy of 94.3%. four NVIDIA GTX 1080 Ti GPUs to speed up the learning process. over 50 epochs was 10 days, 7 h, 14 min, and 20 s. Single Epoch Time 4 hours 56 minutes 41 seconds Yoon, Lee, Oh, Kim, Lee, Chang and Sohn (2019)

The DL algorithm used in the present study, trained on part of the dataset, was able to correctly assign 95.28% of the test cases. Sena et al. (2019).

conditional generative adversarial networks. The average precision, sensitivity, and F1 score during validation was 95.13%, 93.05%, and 94.02% and for an external test dataset was 98.75%, 88.53%, and 93.31%, Tavolara, Niazi, Arole, Chen, Frankel and Gurcan (2019).

In addition to CNN based learning, we also evaluated our framework using some handcrafted texture features. We also got the same finding from our experimental results with handcrafted features. DenseNet Accuracy: 81.9%, U-Net & GoogLeNet Accuracy: 85%, ResNet50 Accuracy: 84.00% Awan, Al-Maadeed, Al-Saady and Bouridane (2020)

ResNet-18, ResNet-34 ResNet-50, ResNet 101, VGG 19 and Alex-Net are used to classify the input image. Accuracy of 98.8%,99.18 %, 99.6%,99.8%, 98.93% and 97.26% Abbas, Bukhari, Syed and Shah (2020).

The accuracy (93.91%) of ResNet-50 was the highest which is followed by ResNet-30 and ResNet-18 with the accuracy of 93.04% each Bukhari, Syed, Bokhari, Hussain, Armaghan and Shah (2020).

CNN acc. 93.7%, CapsNet, 92.3%, TMA+CNN+CapsNet 95.3%. Nguyen, Blank, Lugli and Zlobec (2020).

The CNN model training and validation accuracy of 96.11% and 97.2% are obtained. Hatuwal and Thapa (2020).

the MFF-CNN based on shearlet transform can achieve the identification accuracy of 96% and average F-1 score of 0.9594. Liang, Ren, Yang, Feng and Li (2020).

The method has achieved accurate results (94.52%) by the Resnet121. Dif and Elberrichi (2020).

an accuracy of 99.6%, 96.2% for CNN and VGG16. Qasim, Al-Sameai, Ali and Hassan (2020).

existing methods remain limited when faced with the high resolution and size of Whole Slide Images (WSIs) coupled with the lack of richly annotated datasets. Hamida, Devanne, Weber, Truntzer, Derangère, Ghiringhelli, Forestier and Wemmert (2021).

The DHS-CapsNet achieved better results of 99.23% compared to traditional CapsNet (85.55%). Adu, Yu, Cai, Owusu-Agyemang, Twumasi and Wang (2021).

a hybrid classification model including inception_v3 network, hog and daisy feature extraction modules show that an accuracy of 99.60%. Chen, Huang, Huang and Zhang (2021).

DenseNet-121, the highest accuracy was 98.53%, while ResNet-50 got 94%. Sarwinda, Bustamam, Paradisa, Argyadiva and Mangunwardoyo (2020).

CNN, 96.33% peak classification accuracy. Masud, Sikder, Nahid, Bairagi and AlZain (2021).

A pretrained neural network (AlexNet) was tuned by modifying the four of its layers before training it on the dataset. accuracy of 98.4%. Mehmood, Ghazal, Khan, Zubair, Naseem, Faiz and Ahmad (2022).

The models achieved an accuracy level of VGG16, ResNet50V2, DenseNet201 and Ensemble Transfer Learning were 62%, 90%, 89% and 91%. Phankokkruad (2021).

After combining the results of both CNNs, accuracies that range from 89.66% up to 99.62%. Roberto, Lumini, Neves and do Nascimento (2021).

Ensemble Deep Neural Network to Tumor in Colorectal Histology images. we achieved accuracy of 99.13%. Ghosh et al. (2021).

modified DenseNet121 architecture are used for this purpose. An accuracy of 97.2%. Sarkar, Hazra and Das (2021).

The overall accuracy rate obtained from the DarkNet-19 model as a result of the classification was 96.72%. Toğaçar (2021).

ResNet50 achieved 94.86% accuracy. Tsai and Tao (2021).

deep learning model based on a Faster Region Based Convolutional Neural Network (Faster-RCNN) AUC of 0.917 in the validation cohort, with excellent sensitivity (97.4%). Ho et al. (2022).

seven pre-trained convolution neural network (CNN) models, including MobileNet, VGG-19, ResNet 101, DenseNet 121, DenseNet 169, Inception V3, InceptionResNet V2, and MobileNetV2 for classification of lung cancer. ResNet 101 had the best accuracy of these CNN version, at 98.67%. Shandilya and Nayak (2022).

the average accuracy rate for VGG16, VGG19, MobileNet, DenseNet169, and DenseNet201 is 98.35%, 98.05%, 99.30%, 98.40%, and 99.25%. Talukder, Islam, Uddin, Akhter, Hasan and Moni (2022).

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