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Penerapan Machine Learning untuk Mengetahui Kelangsungan Hidup Pasien Gagal Jantung (*Kardiovaskular*) Menggunakan Kreatinin Serum dan Fraksi Ejeksi

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ABSTRAK

Penyakit *kardiovaskular* menyebabkan kematian di seluruh dunia setiap tahunnya, yang sebagian besar bermanifestasi terutama sebagai serangan jantung atau gagal jantung. Gagal jantung (HF) terjadi ketika jantung tidak dapat memompa cukup darah untuk memenuhi kebutuhan tubuh. Catatan kesehatan elektronik yang tersedia dapat digunakan untuk mengukur gejala, karakteristik fisik, nilai laboratorium, dan melakukan analisis biostatistik untuk mengungkap pola dan hubungan yang tidak diketahui oleh dokter umum. Secara khusus, *Machine Learning* dapat memprediksi kelangsungan hidup pasien berdasarkan data dan mempersonalisasi karakteristik utama rekam medis. Artikel ini menganalisis kumpulan data 299 pasien gagal jantung dengan menerapkan algorithma machine learning menggunakan algoritma *artificial neural network* berbasis *adaboost* untuk lebih meningkatkan akurasi pada algoritma *artificial neural network* (ANN). Pada hasil eksperiment pada penelitian ini didapatkan akurasi algorithma *artificial neural network* (ANN) berbasis adaboost menjadi sangat signifikan dengan hasil akurasi menjadi 81.01%

Keywords:
Cardiovascular,
serum creatinine,
ejection fraction,
medical records,
machine learning,

ABSTRACT

Cardiovascular diseases cause deaths worldwide every year, most of which manifest primarily as heart attacks or heart failure. Heart failure (HF) occurs when the heart cannot pump enough blood to meet the body's needs. Available electronic health records can measure symptoms, physical characteristics, and laboratory values, and perform biostatistical analysis to uncover patterns and relationships unknown to general practitioners. In particular, Machine Learning can predict patient survival based on data and personalize key characteristics of medical records. This article analyzes a data set of 299 heart failure patients by applying machine learning algorithms using an Adaboost-based artificial neural network algorithm to improve further the accuracy of the artificial neural network (ANN) algorithm. In the experimental results of this study, it was found that the accuracy of the AdaBoost-based artificial neural network (ANN) algorithm became very significant with an accuracy result of 81.01%.

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1. PENDAHULUAN

Penyakit *kardiovaskular* (CVD)[1] [2] adalah penyakit jantung dan pembuluh darah, termasuk penyakit arteri koroner (serangan jantung), penyakit *serebrovaskular* (stroke), gagal jantung (HF), dan jenis kondisi medis lainnya Secara keseluruhan, sekitar 17 orang meninggal karena penyakit *kardiovaskular*. 4,444 miliar orang meninggal di seluruh dunia setiap tahunnya, dengan angka kematian meningkat untuk pertama kalinya dalam 50 tahun terakhir Secara khusus, gagal jantung [3], [4] terjadi ketika jantung tidak dapat memompa cukup darah ke tubuh, biasanya disebabkan oleh diabetes, tekanan darah tinggi, atau masalah atau penyakit jantung lainnya. Komunitas klinis mengklasifikasikan gagal jantung menjadi dua jenis berdasarkan nilai fraksi ejeksi, atau persentase darah yang dipompa keluar jantung selama gagal jantung.[3], [4], [5], [6]

Kontraksi dinyatakan sebagai persentase nilai fisiologis antara 50% dan 75%. Yang pertama adalah gagal jantung karena berkurangnya fraksi ejeksi (HFrEF), yang dulu disebut disfungsi sistolik ventrikel kiri (LV) atau gagal jantung karena gagal jantung sistolik, ditandai dengan fraksi ejeksi kurang dari 40%. Yang terakhir adalah gagal jantung dengan fraksi ejeksi yang diawetkan (HFpEF), yang sebelumnya disebut gagal jantung [1], [7], [8]*diastolik* atau gagal jantung fraksi ejeksi normal. Dalam hal ini, ventrikel kiri berkontraksi secara normal selama *sistol*, namun selama *diastol ventrikel* menjadi kaku dan tidak berelaksasi secara normal, sehingga terjadi gangguan pengisian Untuk menilai perkembangan penyakit secara kuantitatif, dokter mengandalkan klasifikasi fungsional New *York Heart Association* (NYHA). Klasifikasi ini mencakup empat tahap, dari aktivitas normal tanpa gejala (Kelas I) hingga tahap di mana beberapa aktivitas fisik menyebabkan ketidaknyamanan dan timbul gejala. Istirahat (kelas IV). [1], [7], [8], [9], [10], [11], [12], [13], [14] Meskipun penggunaannya tersebar luas, tidak ada metode yang konsisten untuk menilai skor NYHA, dan klasifikasi ini tidak dapat memprediksi secara andal karakteristik dasar seperti jarak berjalan kaki atau toleransi olahraga dalam tes formal. Mengingat pentingnya organ vital seperti jantung, prediksi gagal jantung telah menjadi prioritas bagi dokter dan profesional medis, namun sejauh ini prediksi gagal jantung terkait gagal jantung dalam praktik klinis masih tetap biasanya akurasi yang tinggi tidak dapat dicapai. Dalam konteks ini, catatan kesehatan elektronik (EHRs, juga dikenal sebagai catatan medis) adalah sumber informasi yang berguna, tidak hanya untuk penelitian tetapi juga untuk membantu mengungkap korelasi dan hubungan yang tersembunyi dan tidak jelas antara data pasien. dan untuk menghilangkan prasangka mitos tradisional tentang praktik klinis dan faktor risiko. [15]

Untuk mencapai tujuan ini, beberapa studi skrining yang menargetkan penyakit dan demografi berbeda serta sumber data berbeda telah dilakukan dalam beberapa tahun terakhir untuk meningkatkan pengetahuan tentang faktor risiko. Diantaranya, perlu disebutkan studi PLIC. Dalam penelitian ini, EHR, tes darah, 4*.444 polimorfisme nukleotida* tunggal (SNP), pencitraan *ultrasonografi karotis*, dan data *metagenomik* dikumpulkan dalam skrining *longitudina*l pada empat kunjungan selama periode 15 hingga 15 tahun. Milan (Italia, Uni Eropa) mendukung Penilaian risiko penyakit *kardiovaskular* yang lebih baik. *Machine Learning*, terutama bila diterapkan pada rekam medis, dapat menjadi alat yang efektif untuk memprediksi kelangsungan hidup dan mendeteksi gambaran klinis utama (atau gambaran klinis terpenting) pada pasien dengan gejala gagal jantung [18[15], 19], risiko (atau faktor risiko) yang dapat menyebabkan gagal jantung. Para ilmuwan telah mengembangkan prediksi klinis, serta prediksi klinis ketika diterapkan pada rekam medis. Machine learning juga dapat digunakan untuk kekuatan prediksi fitur atau dikombinasikan dengan pencitraan. Selain itu, studi tentang pembelajaran mendalam dan meta-analisis untuk aplikasi di bidang ini juga baru-baru ini muncul dalam literatur. [2], [3], [15], [16], [17], [18], [19], [20], [22],

Peningkatan kinerja spesialis manusia terus berlanjut hingga saat ini dalam hal mencapai akurasi prediksi yang tinggi dalam mengidentifikasi faktor pendorong, meskipun akurasi dalam pemodelan kelangsungan hidup pada gagal jantung (dan CVD secara umum) [2]masih rendah. Sebagian besar model yang dikembangkan untuk tujuan ini hanya mencapai akurasi sedang dan memiliki interpretasi variabel prediktor yang terbatas. Model Baru menunjukkan peningkatan, terutama ketika hasil kelangsungan hidup digabungkan dengan tujuan tambahan misalnya rawat inap. Meskipun para ilmuwan telah mengidentifikasi prediktor dan indikator, tidak ada konsensus mengenai dampak relatifnya terhadap prediksi kelangsungan hidup situasi ini sebagian besar disebabkan oleh kurangnya reproduktifitas, sehingga tidak mungkin untuk menarik kesimpulan tegas tentang pentingnya faktor-faktor yang terdeteksi. Selain itu, kurangnya reproduktifitas ini berdampak signifikan pada performa model. [16], [17], [18], [19], [20], [21], [22]

Generalisasi terhadap kumpulan data validasi eksternal seringkali tidak konsisten dan hanya diskriminasi moderat yang dapat dicapai. Akibatnya, 4.444 penilaian risiko yang dikeluarkan dari model mengalami masalah yang sama, sehingga membatasi keandalannya. Ketidakpastian ini menyebabkan berkembangnya skor risiko baru yang muncul dalam literatur dalam beberapa tahun terakhir di antaranya tidak terduga, satu fraksi ejeksi dan satu lagi kreatinin serum. Hal ini dikenal dalam literatur sebagai faktor penting dalam gagal jantung dan juga merupakan biomarker penting pada ginjal. Secara lebih rinci, pertama-tama kami menjelaskan kumpulan data yang dianalisis dan karakteristiknya lalu menjelaskan metode dan peringkat fitur yang

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digunakan untuk prediksi kelangsungan hidup. Bagian hasil menyajikan kinerja prediksi kelangsungan hidup yang dicapai di semua pengklasifikasi menggunakan metode biostatistik tradisional dan *Machine Learning*. Kami melaporkan kinerja prediksi kelangsungan hidup hanya menggunakan fitur terbaik. Selanjutnya, kami melaporkan kasus dan mendiskusikan hasil analisis yang mencakup masa tindak lanjut dari pasien Terakhir [1], [10], [14], [23], [24], [25], [26], [27], [28], [29], [30], [31], [32], [33], [34], [35] .

2. METODE PENELITIAN

Kami menganalisis kumpulan data [2], [36], [37], [38], [39], [40], [41]yang berisi rekam medis dari 299 pasien gagal jantung para pasien terdiri dari 105 wanita dan 194 pria, dan usia mereka berkisar antara 40 dan 95 tahun. Semua 299 pasien mengalami disfungsi sistolik ventrikel kiri dan mengalami gagal jantung sebelumnya yang menempatkan mereka di kelas III atau IV dari klasifikasi Asosiasi Jantung New York (NYHA) dari tahapan gagal jantung dataset ini berisi 13 fitur, yang melaporkan informasi klinis, klinis, tubuh, dan informasi gaya hidup (Tabel 1), yang kami jelaskan secara singkat jelaskan secara singkat di sini. Beberapa fitur bersifat biner: anemia, tinggi tekanan darah tinggi, diabetes, jenis kelamin, dan merokok. Dokter rumah sakit menganggap pasien mengalami anemia jika kadar hematokrit lebih rendah dari 36%. Sayangnya, naskah set data asli tidak memberikan definisi tekanan darah tinggi Mengenai fitur-fiturnya, kreatinin fosfokinase (CPK) menyatakan tingkat enzim CPK dalam darah. Ketika jaringan otot rusak, CPK mengalir ke dalam darah. Oleh karena itu, kadar CPK yang tinggi dalam darah pasien dapat mengindikasikan gagal jantung atau cedera. Fraksi ejeksi menyatakan persentase berapa banyak darah yang dipompa keluar oleh ventrikel kiri pada setiap kontraksi. Kreatinin serum Kreatinin serum adalah produk limbah yang dihasilkan oleh kreatin, ketika otot rusak. Khususnya, dokter fokus pada kreatinin serum dalam darah untuk memeriksa fungsi ginjal. Jika pasien memiliki kadar kreatinin serum yang tinggi, itu dapat mengindikasikan disfungsi ginjal. Sodium adalah mineral yang berfungsi untuk berfungsinya otot dan saraf. Tes natrium serum adalah pemeriksaan darah rutin yang menunjukkan apakah pasien memiliki kadar natrium yang normal dalam darah. Kadar natrium dalam darah yang tidak normal mungkin disebabkan oleh gagal jantung. Peristiwa kematian yang kami gunakan sebagai target dalam studi ini, adalah apakah pasien meninggal atau selamat sebelum akhir periode tindak lanjut, yaitu rata-rata 130 hari [43], [44], [45], [46], [47], [48], [50]

age	anaemia	creatinine_phosphokinase	diabetes	ejection_fraction	high_blood_pressure	platelets	serum_creatinine	serum_sodium	sex	smoking	time	DEATH_EVENT
75	0	582	0	20	1	265000	1,9	130	1	0	4	DEATH
55	0	7861	0	38	0	263358,03	1,1	136	1	0	6	DEATH
65	0	146	0	20	0	162000	1,3	129	1	1	7	DEATH
50	1	111	0	20	0	210000	1,9	137	1	0	7	DEATH
65	1	160	1	20	0	327000	2,7	116	0	0	8	DEATH
90	1	47	0	40	1	204000	2,1	132	1	1	8	DEATH
75	1	246	0	15	0	127000	1,2	137	1	0	10	DEATH
60	1	315	1	60	0	454000	1,1	131	1	1	10	DEATH
65	0	157	0	65	0	263358,03	1,5	138	0	0	10	DEATH
80	1	123	0	35	1	388000	9,4	133	1	1	10	DEATH
75	1	81	0	38	1	368000	4	131	1	1	10	DEATH
62	0	231	0	25	1	253000	0,9	140	1	1	10	DEATH
45	1	981	0	30	0	136000	1,1	137	1	0	11	DEATH
50	1	168	0	38	1	276000	1,1	137	1	0	11	DEATH
49	1	80	0	30	1	427000	1	138	0	0	12	NO DEATH
82	1	379	0	50	0	47000	1,3	136	1	0	13	DEATH
87	1	149	0	38	0	262000	0,9	140	1	0	14	DEATH
45	0	582	0	14	0	166000	0,8	127	1	0	14	DEATH
70	1	125	0	25	1	237000	1	140	0	0	15	DEATH
48	1	582	1	55	0	87000	1,9	121	0	0	15	DEATH
65	1	52	0	25	1	276000	1,3	137	0	0	16	NO DEATH
65	1	128	1	30	1	297000	1,6	136	0	0	20	DEATH
68	1	220	0	35	1	289000	0,9	140	1	1	20	DEATH
53	0	63	1	60	0	368000	0,8	135	1	0	22	NO DEATH
75	0	582	1	30	1	263358,03	1,83	134	0	0	23	DEATH
80	0	148	1	38	0	149000	1,9	144	1	1	23	DEATH
95	1	112	0	40	1	196000	1	138	0	0	24	DEATH
70	0	122	1	45	1	284000	1,3	136	1	1	26	DEATH
58	1	60	0	38	0	153000	5,8	134	1	0	26	DEATH
82	0	70	1	30	0	200000	1,2	132	1	1	26	DEATH
94	0	582	1	38	1	263358,03	1,83	134	1	0	27	DEATH
85	0	23	0	45	0	360000	3	132	1	0	28	DEATH
50	1	249	1	35	1	319000	1	128	0	0	28	DEATH
50	1	159	1	30	0	302000	1,2	138	0	0	29	NO DEATH
65	0	94	1	50	1	188000	1	140	1	0	29	DEATH

Gambar1. Dataset 1

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	D	E	F	G	H	I	J	K	L	M	N
272	1	30	1	263358,03	1,6	130	1	1	244	NO DEATH	
273	1	40	0	221000	0,9	134	0	0	244	NO DEATH	
274	0	38	0	215000	1,2	133	0	0	245	NO DEATH	
275	0	40	0	189000	0,7	140	1	0	245	NO DEATH	
276	1	30	0	150000	1	137	1	1	245	NO DEATH	
277	0	38	1	422000	0,8	137	0	0	245	NO DEATH	
278	0	35	0	327000	1,1	142	0	0	245	NO DEATH	
279	1	38	0	25100	1,1	140	1	0	246	NO DEATH	
280	1	30	0	232000	0,7	136	0	0	246	NO DEATH	
281	1	38	0	451000	1,3	136	0	0	246	NO DEATH	
282	1	40	0	241000	1	137	1	0	247	NO DEATH	
283	0	40	0	51000	2,7	136	1	1	250	NO DEATH	
284	0	30	0	215000	3,8	128	1	1	250	NO DEATH	
285	0	38	0	263358,03	1,1	138	1	1	250	NO DEATH	
286	0	40	0	279000	0,8	141	1	0	250	NO DEATH	
287	1	40	0	336000	1,2	135	1	0	250	NO DEATH	
288	0	35	0	279000	1,7	140	1	0	250	NO DEATH	
289	1	55	0	543000	1	132	0	0	250	NO DEATH	
290	1	35	0	263358,03	1,1	142	0	0	256	NO DEATH	
291	0	38	0	390000	0,9	144	0	0	256	NO DEATH	
292	1	55	0	222000	0,8	141	0	0	257	NO DEATH	
293	0	35	0	133000	1,4	139	1	0	258	NO DEATH	
294	1	38	0	382000	1	140	1	1	258	NO DEATH	
295	1	35	0	179000	0,9	136	1	1	270	NO DEATH	
296	1	38	1	155000	1,1	143	1	1	270	NO DEATH	
297	0	38	0	270000	1,2	139	0	0	271	NO DEATH	
298	1	60	0	742000	0,8	138	0	0	278	NO DEATH	
299	0	38	0	140000	1,4	140	1	1	280	NO DEATH	
300	0	45	0	395000	1,6	136	1	1	285	NO DEATH	

Gambar2. Dataset 2

Tabel 2 Penjelasan Dataset

Feature	Explanation	Measurement	Range
Age	Age of the patient	Years	[40, ..., 95]
Anaemia	Anaemia Decrease of red blood cells or hemoglobin	Boolean	0, 1
High blood pressure	If a patient has hypertension	Boolean	0, 1
Creatinine phosphokinase (CPK)	phosphokinase Level of the CPK enzyme in the blood	mcg/L	[23, ..., 7861]
Diabetes	If the patient has diabetes	Boolean	0, 1
Ejection fraction	Percentage of blood leaving	Percentage	[14, ..., 80]
Sex	Woman or man	Binary	0, 1
Platelets	Platelets in the blood	kiloplatelets/mL	[25.01, ..., 850.00]
Serum creatinine	Level of creatinine in the blood	mg/dL	[0.50, ..., 9.40]
Serum sodium	Level of sodium in the blood	mEq/L	[114, ..., 148]
Smoking	If the patient smokes	Boolean	0, 1
Time	Follow-up period	Days	[4,...,285]
(target) death event	**(target) death event If the patient died during the follow-up period**	**Boolean 0, 1**	**0, 1**

Artikel kumpulan data asli tidak merinci apakah pasien menderita penyakit ginjal primer, juga tidak memberikan informasi tambahan tentang jenis tindak lanjut yang dilakukan. Mengenai dataset tidak seimbang , 203 pasien selamat (kejadian kematian = 0) dan 96 pasien meninggal (kejadian kematian = 1). Statistik adalah 32,11% positif dan 67,89% negatif. Kami merepresentasikan kumpulan data ini sebagai tabel dengan 299 baris (pasien), dan 13 kolom (fitur). Agar lebih jelas, kami sedikit mengubah nama beberapa fitur di dataset asli. Tabel 2 dan 3 melaporkan data kuantitatif dari kumpulan data. [59], [60], [61], [62], [63], [64], [65], [66], [67], [68], [69], [70], [71], [72], [73], [74], [75], [76]

Bagian ini dimulai dengan klasifikasi kelangsungan menggunakan machine learning untuk pemeringkatan fitur dengan membuang setiap periode tindak lanjut untuk pasien. Selanjutnya, menjelaskan algoritma artificial neural network berbasis adaboost [3], [42], [43], [44], [45], [46], [47], [48], [49]yang digunakan untuk memprediksi kelangsungan hidup dan melakukan pemeringkatan fitur sebagai fungsi waktu tindak lanjut.

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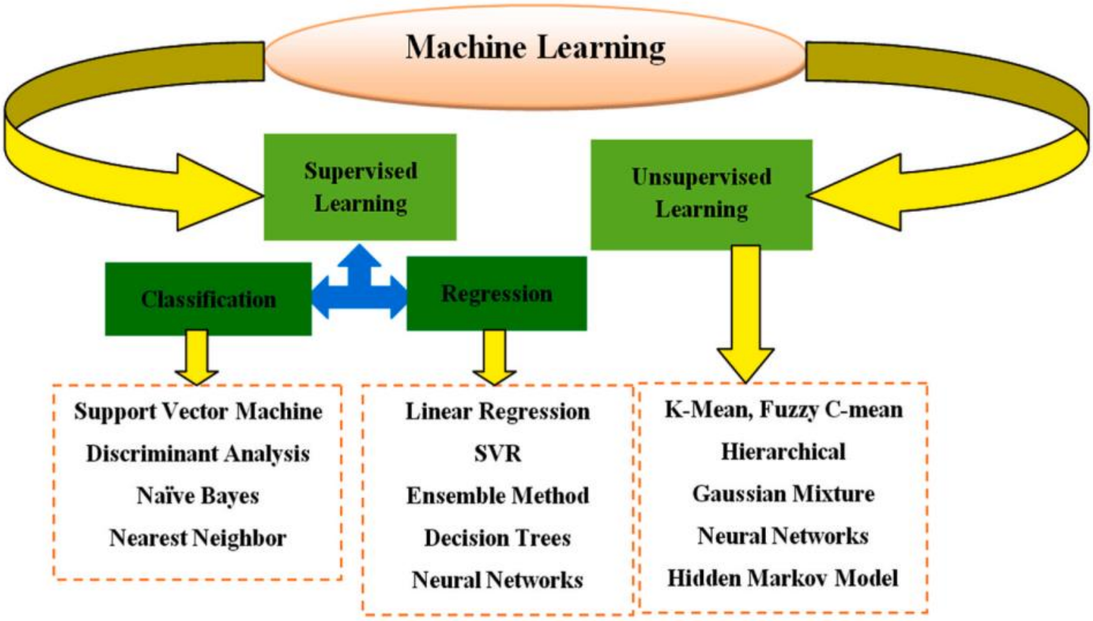
Pengklasifikasi prediksi kelangsungan hidup berfokus pada prediksi kelangsungan hidup pasien selama masa tindak lanjut. Kami menerapkan metode dalam *framework rapidminer*.

Terkait Machine Learning, kami menggunakan algorithma artificial neural network berbasis adaboost. Hal ini karena ternyata memadukan kedua algorithma ADABOOST dengan ANN berkinerja terbaik dan akurat di seluruh kumpulan data yang besar dan kompleks.[2], [3], [15], [16], [17], [18], [19], [20], [22], [43], [44], [45], [46], [47], [48], [50], [51], [52], [53], [54], [55], [56], [57], [58], [59], [60], [61], [62], [63], [64], [65], [66], [67], [68], [69], [70], [71], [72], [73], [74], [75], [76]



Gambar 3. Machine Learning [16], [49], [77], [78], [79], [80], [81], [82], [83], [84]

Adaptive boosting (AdaBoost) adalah algoritma pembelajaran yang dirumuskan oleh Freund dan Schapire yang dapat digunakan dalam kombinasi dengan algoritma pembelajaran lain untuk menciptakan algoritma pembelajaran yang lebih baik. [85], [86], [87], [88], [89], [90], [91]

Given: $(x_1, y_1), \ldots, (x_m, y_m)$ where $x_i \in \mathscr{X}$, $y_i \in \{-1, +1\}$.
Initialize: $D_1(i) = 1/m$ for $i = 1, \ldots, m$.
For $t = 1, \ldots, T$:

- Train weak learner using distribution D_t.
- Get weak hypothesis $h_t : \mathscr{X} \to \{-1, +1\}$.
- Aim: select h_t with low weighted error:

$$\varepsilon_t = \Pr_{i \sim D_t}\left[h_t(x_i) \neq y_i\right].$$

- Choose $\alpha_t = \frac{1}{2} \ln\left(\frac{1-\varepsilon_t}{\varepsilon_t}\right)$.
- Update, for $i = 1, \ldots, m$:

$$D_{t+1}(i) = \frac{D_t(i)\exp(-\alpha_t y_i h_t(x_i))}{Z_t}$$

where Z_t is a normalization factor (chosen so that D_{t+1} will be a distribution).

Output the final hypothesis:

$$H(x) = \operatorname{sign}\left(\sum_{t=1}^{T} \alpha_t h_t(x)\right).$$

Gambar 4. Algorithma Adaboost [92], [93], [94], [95], [96], [97], [98], [99]

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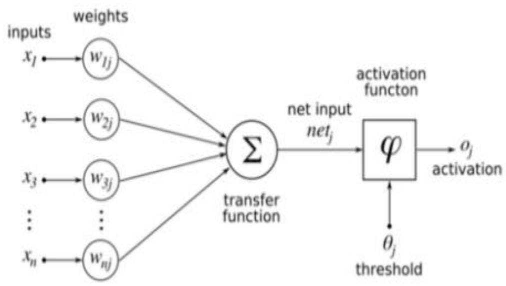
Artificial Neural Network (ANN) [100], [101], [102], [103], [104], [105], [106], [107], [108], [109], [110], [111], [112], [113], [114], [115], [116], [117], [118], [119], [120], [121], [122], [123], [124], [125], [126], [127], [128], [129], [130]merupakan sebuah sistem cerdas yang digunakan untuk mengolah informasi yang merupakan perkembangan dari generalisasi model matematika. Prinsip kerja ANN terinspirasi dari prinsip kerja sistem jaringan saraf (neural network) manusia. Para ilmuan menciptakan algoritma matematis yang bekerja menyerupai pola kerja saraf (neuron) tersebut, maka digunakanlah nama Artificial Neural Network, atau dalam Bahasa Indonesia biasa disebut Jaringan Saraf Tiruan (JST). Gambar. 3 dibawah menggambarkan kemiripan arsitektur ANN dengan dengan sistem jaringan saraf pada tubuh manusia,



Gambar 5. Struktur ANN [131]

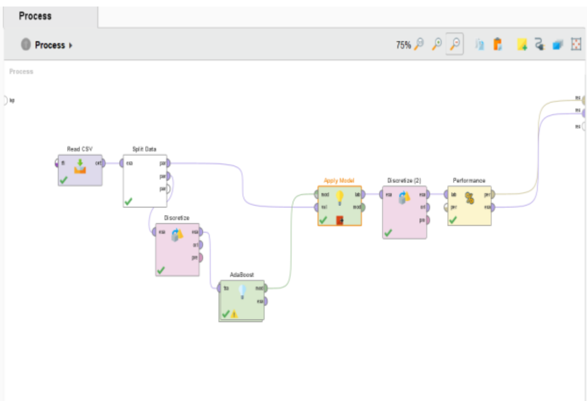
. Adapun Kelebihan dan Kekurangan Algorithma Artificial Neural Netowrk. Gambar 3

Advantages
1. Neural network models require less formal statistical training to develop
2. Neural network models can implicitly detect complex nonlinear relationships between independent and dependent variables
3. Neural network models have the ability to detect all possible interactions between predictor variables
4. Neural networks can be developed using multiple different training algorithms

Disadvantages
1. Neural networks are a “black box” and have limited ability to explicitly identify possible causal relationships
2. Neural networks models may be more difficult to use in the field
3. Neural network modeling requires greater computational resources
4. Neural network models are prone to overfitting
5. Neural network model development is empirical, and many methodological issues remain to be resolved

Gambar 6. Kelebihan dan Kekurangan Neural Network (ANN) [131]

3. HASIL DAN ANALISIS



Gambar 7. Proses Analysis 1

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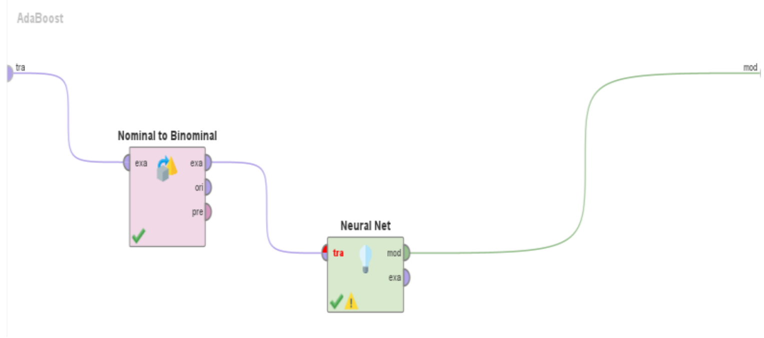
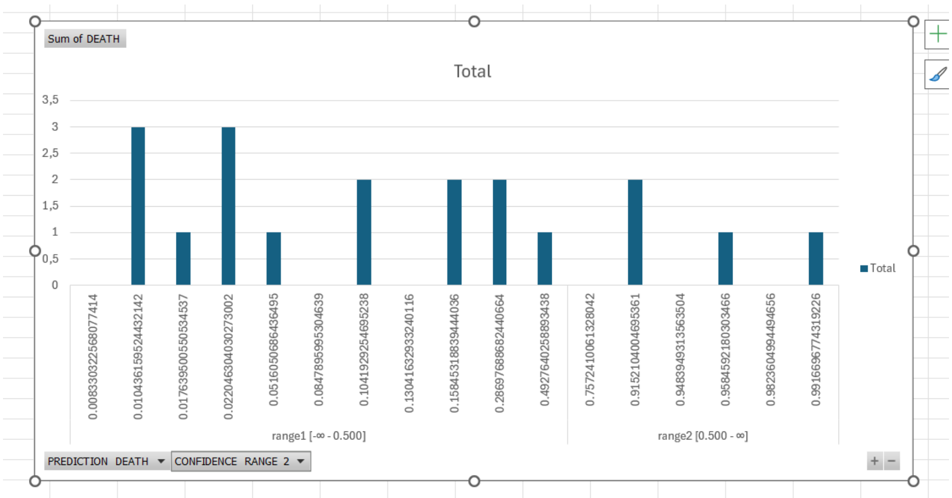


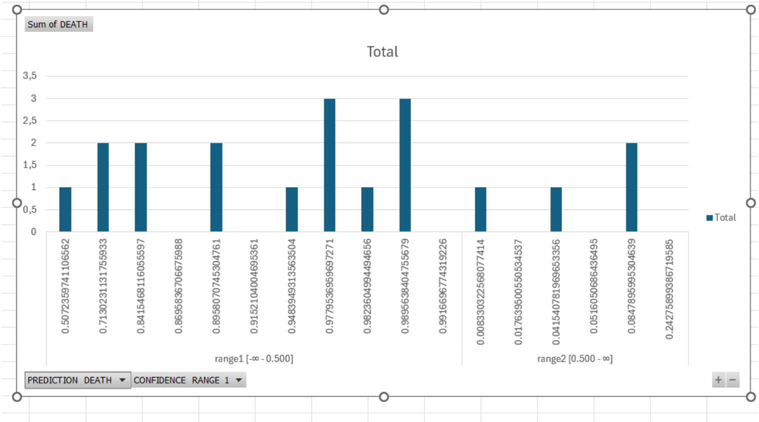
Gambar 8. Proses Analysis 2

age	anaemia	creatinine_p...	diabetes	ejection_fra...	high_blood_...	platelets	serum_creat...	serum_sodi...	sex	smoking	time
range2 [67.500...	range1 [-∞ - 0....	range1 [-∞ - 3...	range1 [-∞ - 0....	range1 [-∞ - 4...	range2 [0.500 -...	range1 [-∞ - 3...	range1 [-∞ - 5....	range2 [129 - ...	range2 [0.500 -...	range1 [-∞ - 0....	range1 [-∞ - 1...
range1 [-∞ - 6...	range2 [0.500 -...	range1 [-∞ - 3...	range1 [-∞ - 0....	range1 [-∞ - 4...	range1 [-∞ - 0....	range1 [-∞ - 3...	range1 [-∞ - 5....	range2 [129 - ...	range2 [0.500 -...	range1 [-∞ - 0....	range1 [-∞ - 1...
range1 [-∞ - 6...	range2 [0.500 -...	range1 [-∞ - 3...	range2 [0.500 -...	range1 [-∞ - 4...	range1 [-∞ - 0....	range1 [-∞ - 3...	range1 [-∞ - 5....	range1 [-∞ - 1...	range1 [-∞ - 0....	range1 [-∞ - 0....	range1 [-∞ - 1...
range2 [67.500...	range2 [0.500 -...	range1 [-∞ - 3...	range1 [-∞ - 0....	range1 [-∞ - 4...	range2 [0.500 -...	range1 [-∞ - 3...	range1 [-∞ - 5....	range2 [129 - ...	range2 [0.500 -...	range2 [0.500 -...	range1 [-∞ - 1...
range2 [67.500...	range2 [0.500 -...	range1 [-∞ - 3...	range1 [-∞ - 0....	range1 [-∞ - 4...	range1 [-∞ - 0....	range1 [-∞ - 3...	range1 [-∞ - 5....	range2 [129 - ...	range2 [0.500 -...	range1 [-∞ - 0....	range1 [-∞ - 1...
range1 [-∞ - 6...	range2 [0.500 -...	range1 [-∞ - 3...	range2 [0.500 -...	range2 [47.500...	range1 [-∞ - 0....	range2 [38355...	range1 [-∞ - 5....	range2 [129 - ...	range2 [0.500 -...	range2 [0.500 -...	range1 [-∞ - 1...
range1 [-∞ - 6...	range1 [-∞ - 0....	range1 [-∞ - 3...	range1 [-∞ - 0....	range2 [47.500...	range1 [-∞ - 0....	range1 [-∞ - 3...	range1 [-∞ - 5....	range2 [129 - ...	range1 [-∞ - 0....	range1 [-∞ - 0....	range1 [-∞ - 1...
range2 [67.500...	range2 [0.500 -...	range1 [-∞ - 3...	range1 [-∞ - 0....	range1 [-∞ - 4...	range2 [0.500 -...	range2 [38355...	range2 [5.050 -...	range2 [129 - ...	range2 [0.500 -...	range2 [0.500 -...	range1 [-∞ - 1...
range1 [-∞ - 6...	range2 [0.500 -...	range1 [-∞ - 3...	range1 [-∞ - 0....	range1 [-∞ - 4...	range1 [-∞ - 0....	range1 [-∞ - 3...	range1 [-∞ - 5....	range2 [129 - ...	range2 [0.500 -...	range1 [-∞ - 0....	range1 [-∞ - 1...
range1 [-∞ - 6...	range2 [0.500 -...	range1 [-∞ - 3...	range1 [-∞ - 0....	range1 [-∞ - 4...	range2 [0.500 -...	range1 [-∞ - 3...	range1 [-∞ - 5....	range2 [129 - ...	range2 [0.500 -...	range1 [-∞ - 0....	range1 [-∞ - 1...
range2 [67.500...	range2 [0.500 -...	range1 [-∞ - 3...	range1 [-∞ - 0....	range1 [-∞ - 4...	range1 [-∞ - 0....	range1 [-∞ - 3...	range1 [-∞ - 5....	range2 [129 - ...	range2 [0.500 -...	range1 [-∞ - 0....	range1 [-∞ - 1...
range2 [67.500...	range2 [0.500 -...	range1 [-∞ - 3...	range1 [-∞ - 0....	range1 [-∞ - 4...	range2 [0.500 -...	range1 [-∞ - 3...	range1 [-∞ - 5....	range2 [129 - ...	range1 [-∞ - 0....	range1 [-∞ - 0....	range1 [-∞ - 1...
range2 [67.500...	range1 [-∞ - 0....	range1 [-∞ - 3...	range2 [0.500 -...	range1 [-∞ - 4...	range2 [0.500 -...	range1 [-∞ - 3...	range1 [-∞ - 5....	range2 [129 - ...	range1 [-∞ - 0....	range1 [-∞ - 0....	range1 [-∞ - 1...
range2 [67.500...	range1 [-∞ - 0....	range1 [-∞ - 3...	range2 [0.500 -...	range1 [-∞ - 4...	range1 [-∞ - 0....	range1 [-∞ - 3...	range1 [-∞ - 5....	range2 [129 - ...	range2 [0.500 -...	range2 [0.500 -...	range1 [-∞ - 1...
range2 [67.500...	range1 [-∞ - 0....	range1 [-∞ - 3...	range2 [0.500 -...	range1 [-∞ - 4...	range1 [-∞ - 0....	range1 [-∞ - 3...	range1 [-∞ - 5....	range2 [129 - ...	range2 [0.500 -...	range2 [0.500 -...	range1 [-∞ - 1...
range2 [67.500...	range1 [-∞ - 0....	range1 [-∞ - 3...	range2 [0.500 -...	range1 [-∞ - 4...	range2 [0.500 -...	range1 [-∞ - 3...	range1 [-∞ - 5....	range2 [129 - ...	range2 [0.500 -...	range1 [-∞ - 0....	range1 [-∞ - 1...
range2 [67.500...	range1 [-∞ - 0....	range1 [-∞ - 3...	range1 [-∞ - 0....	range1 [-∞ - 4...	range1 [-∞ - 0....	range1 [-∞ - 3...	range1 [-∞ - 5....	range2 [129 - ...	range2 [0.500 -...	range1 [-∞ - 0....	range1 [-∞ - 1...
range1 [-∞ - 6...	range2 [0.500 -...	range1 [-∞ - 3...	range2 [0.500 -...	range1 [-∞ - 4...	range1 [-∞ - 0....	range1 [-∞ - 3...	range1 [-∞ - 5....	range2 [129 - ...	range1 [-∞ - 0....	range1 [-∞ - 0....	range1 [-∞ - 1...

Gambar. 9 Hasil



Gambar 10. Grafik Prediksi Death pada Range 2



Gambar. 11. Grafik Prediksi Death pada Range 1.

accuracy: 81.01%

	true range1 [-∞ - 0.500]	true range2 [0.500 - ∞]	class precision
pred. range1 [-∞ - 0.500]	111	23	82.84%
pred. range2 [0.500 - ∞]	11	34	75.56%
class recall	90.98%	59.65%	

Gambar. 12 Akurasi

PerformanceVector

```
PerformanceVector:
accuracy: 81.01%
ConfusionMatrix:
True:   range1 [-∞ - 0.500]     range2 [0.500 - ∞]
range1 [-∞ - 0.500]:    111     23
range2 [0.500 - ∞]:     11      34
root_mean_squared_error: 0.436 +/- 0.000
```

Gambar. 13 Performance

Hasil menunjukkan bahwa kelangsungan hidup pasien gagal jantung dapat diprediksi hanya berdasarkan kreatinin serum dan fraksi ejeksi, namun juga prediksi yang dibuat berdasarkan dua karakteristik ini saja lebih baik dibandingkan berdasarkan karakteristik tersebut lebih akurat dari prediksi yang dibuat.

4. KESIMPULAN

Dalam penelitian ini, fakta bahwa Penerapan machine learning berbasis adaboost untuk lebih meningkatkan akurasi pada algoritma artificial neural network (ANN) untuk memprediksi memilih fraksi ejeksi dan kreatinin serum sebagai dua fitur yang paling relevan mendukung relevansi evaluasi fitur yang dilakukan dengan Machine Learning. Selain itu, pendekatan kami menunjukkan bahwa Machine Learning dapat digunakan secara efektif untuk catatan kesehatan elektronik pasien dengan penyakit *kardiovaskular*. Keterbatasan penelitian ini adalah kebutuhan untuk menyediakan ukuran dataset yang kecil (299 pasien). Kumpulan data yang lebih besar memberikan hasil yang lebih andal. Informasi tambahan tentang karakteristik fisik pasien (seperti tinggi badan, berat badan, dan BMI) dan riwayat pekerjaan dapat membantu mengidentifikasi faktor risiko tambahan untuk penyakit *kardiovaskular*. Pada hasil penelitian ini didapatkan akurasi *metode artificial neural network* (ANN) berbasis *adaboost* menjadi sangat signifikan dengan hasil akurasi menjadi 81.01%.

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