



Vidyavardhini's College of Engineering & Technology

Department of Computer Science and Engineering (Data Science)

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Date of Performance:	
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Marks:	
Sign of Faculty:	



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Aim: Clean, Integrate and Transform Electronic Healthcare Records.

Theory:

Data cleaning means fixing bad data in your data set.

Data cleaning is a crucial step in the data analysis process, particularly when it comes to analyzing social media data. Social media data sources such as Twitter, Facebook, Instagram, and LinkedIn are often messy, inconsistent, and contain a lot of noise. Therefore, cleaning the data before analyzing it is essential to ensure the accuracy and validity of the results. Here are some of the commonly used data cleaning techniques in social media analytics:

1. Removing duplicates: Social media platforms generate a lot of redundant data, such as retweets, shares, and likes. Removing these duplicates can help simplify the data and reduce noise.
2. Filtering out spam: Social media is rife with spam content such as promotional posts, advertisements, and irrelevant comments. Removing spam can help improve the quality of the data.
3. Removing irrelevant content: Some social media data may be irrelevant to the research question, such as posts that are not related to the topic of interest. Removing irrelevant content can help narrow down the data and focus on the most relevant information.
4. Standardizing formats: Social media data may come in various formats, such as hashtags, mentions, or emojis. Standardizing these formats can help simplify the data and make it easier to analyze.
5. Correcting errors: Social media data may contain errors, such as misspellings, grammatical errors, or incomplete sentences. Correcting these errors can help improve the accuracy of the data.
6. Handling missing data: Social media data may contain missing values, such as empty fields or null values. Handling missing data can help avoid bias and improve the accuracy of the analysis.

In summary, data cleaning is an essential step in social media analytics. It helps ensure the accuracy and validity of the results by removing duplicates, filtering out spam, removing irrelevant content, standardizing formats, correcting errors, and handling missing data. Bad data could be:

- Empty cells
- Data in the wrong format
- Wrong data
- Duplicates

```
import pandas as pd

df = pd.read_csv('/content/diabetes.csv')

new_df = df.dropna()

print(new_df.to_string())
```

710	3	158	64.0	13	387	31.2	0.295	24	0
711	5	126	78.0	27	22	29.6	0.439	40	0
712	10	129	62.0	36	0	41.2	0.441	38	1
713	0	134	58.0	20	291	26.4	0.352	21	0
714	3	102	74.0	0	0	29.5	0.121	32	0
715	7	187	50.0	33	392	33.9	0.826	34	1
716	3	173	78.0	39	185	33.8	0.970	31	1
717	10	94	72.0	18	0	23.1	0.595	56	0
718	1	108	60.0	46	178	35.5	0.415	24	0
719	5	97	76.0	27	0	35.6	0.378	52	1
720	4	83	86.0	19	0	29.3	0.317	34	0
721	1	114	66.0	36	200	38.1	0.289	21	0
722	1	149	68.0	29	127	29.3	0.349	42	1
723	5	117	86.0	30	105	39.1	0.251	42	0
724	1	111	94.0	0	0	32.8	0.265	45	0
725	4	112	78.0	40	0	39.4	0.236	38	0
726	1	116	78.0	29	180	36.1	0.496	25	0
727	0	141	84.0	26	0	32.4	0.433	22	0
728	2	175	88.0	0	0	22.9	0.326	22	0
729	2	92	52.0	0	0	30.1	0.141	22	0
730	3	130	78.0	23	79	28.4	0.323	34	1
731	8	120	86.0	0	0	28.4	0.259	22	1
732	2	174	88.0	37	120	44.5	0.646	24	1
733	2	106	56.0	27	165	29.0	0.426	22	0
734	2	105	75.0	0	0	23.3	0.560	53	0
735	4	95	60.0	32	0	35.4	0.284	28	0
736	0	126	86.0	27	120	27.4	0.515	21	0
737	8	65	72.0	23	0	32.0	0.600	42	0
738	2	99	60.0	17	160	36.6	0.453	21	0
739	1	102	74.0	0	0	39.5	0.293	42	1
740	11	120	80.0	37	150	42.3	0.785	48	1
741	3	102	44.0	20	94	30.8	0.400	26	0
742	1	109	58.0	18	116	28.5	0.219	22	0
743	9	140	94.0	0	0	32.7	0.734	45	1
744	13	153	88.0	37	140	40.6	1.174	39	0
745	12	100	84.0	33	105	30.0	0.488	46	0
746	1	147	94.0	41	0	49.3	0.358	27	1
747	1	81	74.0	41	57	46.3	1.096	32	0
748	3	187	70.0	22	200	36.4	0.408	36	1
749	6	162	62.0	0	0	24.3	0.178	50	1
750	4	136	70.0	0	0	31.2	1.182	22	1
751	1	121	78.0	39	74	39.0	0.261	28	0
752	3	108	62.0	24	0	26.0	0.223	25	0
753	0	181	88.0	44	510	43.3	0.222	26	1
754	8	154	78.0	32	0	32.4	0.443	45	1
755	1	128	88.0	39	110	36.5	1.057	37	1
756	7	137	90.0	41	0	32.0	0.391	39	0
757	0	123	72.0	0	0	36.3	0.258	52	1
758	1	106	76.0	0	0	37.5	0.197	26	0
759	6	190	92.0	0	0	35.5	0.278	66	1
760	2	88	58.0	26	16	28.4	0.766	22	0
761	9	170	74.0	31	0	44.0	0.403	43	1
762	9	89	62.0	0	0	22.5	0.142	33	0
763	10	101	76.0	48	180	32.9	0.171	63	0
764	2	122	70.0	27	0	36.8	0.340	27	0
765	5	121	72.0	23	112	26.2	0.245	30	0
766	1	126	60.0	0	0	30.1	0.349	47	1
767	1	93	70.0	31	0	30.4	0.315	23	0

```
import pandas as pd

df = pd.read_csv('diabetes.csv')

df.dropna(inplace = True)

print(df.to_string())
```

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DS_exp_01.ipynb - Colaboratory

722	1	149	68.0	29	127	29.3	0.349	42	1
723	5	117	86.0	30	105	39.1	0.251	42	0
724	1	111	94.0	0	0	32.8	0.265	45	0
725	4	112	78.0	40	0	39.4	0.236	38	0
726	1	116	78.0	29	180	36.1	0.496	25	0
727	0	141	84.0	26	0	32.4	0.433	22	0
728	2	175	88.0	0	0	22.9	0.326	22	0
729	2	92	52.0	0	0	30.1	0.141	22	0
730	3	130	78.0	23	79	28.4	0.323	34	1
731	8	120	86.0	0	0	28.4	0.259	22	1
732	2	174	88.0	37	120	44.5	0.646	24	1
733	2	106	56.0	27	165	29.0	0.426	22	0
734	2	105	75.0	0	0	23.3	0.560	53	0
735	4	95	60.0	32	0	35.4	0.284	28	0
736	0	126	86.0	27	120	27.4	0.515	21	0
737	8	65	72.0	23	0	32.0	0.600	42	0
738	2	99	60.0	17	160	36.6	0.453	21	0
739	1	102	74.0	0	0	39.5	0.293	42	1
740	11	120	80.0	37	150	42.3	0.785	48	1
741	3	102	44.0	20	94	30.8	0.400	26	0
742	1	109	58.0	18	116	28.5	0.219	22	0
743	9	140	94.0	0	0	32.7	0.734	45	1
744	13	153	88.0	37	140	40.6	1.174	39	0
745	12	100	84.0	33	105	30.0	0.488	46	0
746	1	147	94.0	41	0	49.3	0.358	27	1
747	1	81	74.0	41	57	46.3	1.096	32	0
748	3	187	70.0	22	200	36.4	0.408	36	1
749	6	162	62.0	0	0	24.3	0.178	50	1
750	4	136	70.0	0	0	31.2	1.182	22	1
751	1	121	78.0	39	74	39.0	0.261	28	0
752	3	108	62.0	24	0	26.0	0.223	25	0
753	0	181	88.0	44	510	43.3	0.222	26	1
754	8	154	78.0	32	0	32.4	0.443	45	1
755	1	128	88.0	39	110	36.5	1.057	37	1
756	7	137	90.0	41	0	32.0	0.391	39	0
757	0	123	72.0	0	0	36.3	0.258	52	1
758	1	106	76.0	0	0	37.5	0.197	26	0
759	6	190	92.0	0	0	35.5	0.278	66	1
760	2	88	58.0	26	16	28.4	0.766	22	0
761	9	170	74.0	31	0	44.0	0.403	43	1
762	9	89	62.0	0	0	22.5	0.142	33	0
763	10	101	76.0	48	180	32.9	0.171	63	0
764	2	122	70.0	27	0	36.8	0.340	27	0
765	5	121	72.0	23	112	26.2	0.245	30	0
766	1	126	60.0	0	0	30.1	0.349	47	1
767	1	93	70.0	31	0	30.4	0.315	23	0

```
df.fillna(130, inplace = True)
print(df.to_string())
```

747	1	81	74.0	41	37	40.3	1.057	37	1
748	3	187	70.0	22	200	36.4	0.408	36	1
749	6	162	62.0	0	0	24.3	0.178	50	1
750	4	136	70.0	0	0	31.2	1.182	22	1
751	1	121	78.0	39	74	39.0	0.261	28	0
752	3	108	62.0	24	0	26.0	0.223	25	0
753	0	181	88.0	44	510	43.3	0.222	26	1
754	8	154	78.0	32	0	32.4	0.443	45	1
755	1	128	88.0	39	110	36.5	1.057	37	1
756	7	137	90.0	41	0	32.0	0.391	39	0
757	0	123	72.0	0	0	36.3	0.258	52	1
758	1	106	76.0	0	0	37.5	0.197	26	0
759	6	190	92.0	0	0	35.5	0.278	66	1
760	2	88	58.0	26	16	28.4	0.766	22	0
761	9	170	74.0	31	0	44.0	0.403	43	1
762	9	89	62.0	0	0	22.5	0.142	33	0
763	10	101	76.0	48	180	32.9	0.171	63	0
764	2	122	70.0	27	0	36.8	0.340	27	0
765	5	121	72.0	23	112	26.2	0.245	30	0
766	1	126	60.0	0	0	30.1	0.349	47	1
767	1	93	70.0	31	0	30.4	0.315	23	0

```
import pandas as pd
```

```
df = pd.read_csv('diabetes.csv')
```

```
df["Glucose"].fillna(130, inplace = True)
print(df.to_string())
```

710	3	158	64.0	13	387	31.2	0.295	24	0
711	5	126	78.0	27	22	29.6	0.439	40	0
712	10	129	62.0	36	0	41.2	0.441	38	1
713	0	134	58.0	20	291	26.4	0.352	21	0
714	3	102	74.0	0	0	29.5	0.121	32	0
715	7	187	50.0	33	392	33.9	0.826	34	1
716	3	173	78.0	39	185	33.8	0.970	31	1
717	10	94	72.0	18	0	23.1	0.595	56	0
718	1	108	60.0	46	178	35.5	0.415	24	0
719	5	97	76.0	27	0	35.6	0.378	52	1
720	4	83	86.0	19	0	29.3	0.317	34	0
721	1	114	66.0	36	200	38.1	0.289	21	0
722	1	149	68.0	29	127	29.3	0.349	42	1
723	5	117	86.0	30	105	39.1	0.251	42	0
724	1	111	94.0	0	0	32.8	0.265	45	0
725	4	112	78.0	40	0	39.4	0.236	38	0
726	1	116	78.0	29	180	36.1	0.496	25	0
727	0	141	84.0	26	0	32.4	0.433	22	0
728	2	175	88.0	0	0	22.9	0.326	22	0
729	2	92	52.0	0	0	30.1	0.141	22	0
730	3	130	78.0	23	79	28.4	0.323	34	1
731	8	120	86.0	0	0	28.4	0.259	22	1
732	2	174	88.0	37	120	44.5	0.646	24	1
733	2	106	56.0	27	165	29.0	0.426	22	0
734	2	105	75.0	0	0	23.3	0.560	53	0
735	4	95	60.0	32	0	35.4	0.284	28	0
736	0	126	86.0	27	120	27.4	0.515	21	0
737	8	65	72.0	23	0	32.0	0.600	42	0
738	2	99	60.0	17	160	36.6	0.453	21	0
739	1	102	74.0	0	0	39.5	0.293	42	1
740	11	120	80.0	37	150	42.3	0.785	48	1
741	3	102	44.0	20	94	30.8	0.400	26	0
742	1	109	58.0	18	116	28.5	0.219	22	0
743	9	140	94.0	0	0	32.7	0.734	45	1
744	13	153	88.0	37	140	40.6	1.174	39	0
745	12	100	84.0	33	105	30.0	0.488	46	0
746	1	147	94.0	41	0	49.3	0.358	27	1
747	1	81	74.0	41	57	46.3	1.096	32	0
748	3	187	70.0	22	200	36.4	0.408	36	1
749	6	162	62.0	0	0	24.3	0.178	50	1
750	4	136	70.0	0	0	31.2	1.182	22	1
751	1	121	78.0	39	74	39.0	0.261	28	0
752	3	108	62.0	24	0	26.0	0.223	25	0
753	0	181	88.0	44	510	43.3	0.222	26	1
754	8	154	78.0	32	0	32.4	0.443	45	1
755	1	128	88.0	39	110	36.5	1.057	37	1
756	7	137	90.0	41	0	32.0	0.391	39	0
757	0	123	72.0	0	0	36.3	0.258	52	1
758	1	106	76.0	0	0	37.5	0.197	26	0
759	6	190	92.0	0	0	35.5	0.278	66	1
760	2	88	58.0	26	16	28.4	0.766	22	0
761	9	170	74.0	31	0	44.0	0.403	43	1
762	9	89	62.0	0	0	22.5	0.142	33	0
763	10	101	76.0	48	180	32.9	0.171	63	0
764	2	122	70.0	27	0	36.8	0.340	27	0
765	5	121	72.0	23	112	26.2	0.245	30	0
766	1	126	60.0	0	0	30.1	0.349	47	1
767	1	93	70.0	31	0	30.4	0.315	23	0

```
x = df["BloodPressure"].mean()
```

```
df["BloodPressure"].fillna(x, inplace = True)
print(df.to_string())
```

710	3	158	64.000000	13	387	31.2	0.295	24	0
711	5	126	78.000000	27	22	29.6	0.439	40	0
712	10	129	62.000000	36	0	41.2	0.441	38	1
713	0	134	58.000000	20	291	26.4	0.352	21	0
714	3	102	74.000000	0	0	29.5	0.121	32	0
715	7	187	50.000000	33	392	33.9	0.826	34	1
716	3	173	78.000000	39	185	33.8	0.970	31	1
717	10	94	72.000000	18	0	23.1	0.595	56	0
718	1	108	60.000000	46	178	35.5	0.415	24	0
719	5	97	76.000000	27	0	35.6	0.378	52	1
720	4	83	86.000000	19	0	29.3	0.317	34	0
721	1	114	66.000000	36	200	38.1	0.289	21	0
722	1	149	68.000000	29	127	29.3	0.349	42	1
723	5	117	86.000000	30	105	39.1	0.251	42	0
724	1	111	94.000000	0	0	32.8	0.265	45	0
725	4	112	78.000000	40	0	39.4	0.236	38	0
726	1	116	78.000000	29	180	36.1	0.496	25	0
727	0	141	84.000000	26	0	32.4	0.433	22	0
728	2	175	88.000000	0	0	22.9	0.326	22	0
729	2	92	52.000000	0	0	30.1	0.141	22	0
730	3	130	78.000000	23	79	28.4	0.323	34	1
731	8	120	86.000000	0	0	28.4	0.259	22	1
732	2	174	88.000000	37	120	44.5	0.646	24	1
733	2	106	56.000000	27	165	29.0	0.426	22	0
734	2	105	75.000000	0	0	23.3	0.560	53	0
735	4	95	60.000000	32	0	35.4	0.284	28	0
736	0	126	86.000000	27	120	27.4	0.515	21	0
737	8	65	72.000000	23	0	32.0	0.600	42	0
738	2	99	60.000000	17	160	36.6	0.453	21	0
739	1	102	74.000000	0	0	39.5	0.293	42	1
740	11	120	80.000000	37	150	42.3	0.785	48	1
741	3	102	44.000000	20	94	30.8	0.400	26	0
742	1	109	58.000000	18	116	28.5	0.219	22	0
743	9	140	94.000000	0	0	32.7	0.734	45	1
744	13	153	88.000000	37	140	40.6	1.174	39	0
745	12	100	84.000000	33	105	30.0	0.488	46	0
746	1	147	94.000000	41	0	49.3	0.358	27	1
747	1	81	74.000000	41	57	46.3	1.096	32	0
748	3	187	70.000000	22	200	36.4	0.408	36	1
749	6	162	62.000000	0	0	24.3	0.178	50	1
750	4	136	70.000000	0	0	31.2	1.182	22	1
751	1	121	78.000000	39	74	39.0	0.261	28	0
752	3	108	62.000000	24	0	26.0	0.223	25	0
753	0	181	88.000000	44	510	43.3	0.222	26	1
754	8	154	78.000000	32	0	32.4	0.443	45	1
755	1	128	88.000000	39	110	36.5	1.057	37	1
756	7	137	90.000000	41	0	32.0	0.391	39	0
757	0	123	72.000000	0	0	36.3	0.258	52	1
758	1	106	76.000000	0	0	37.5	0.197	26	0
759	6	190	92.000000	0	0	35.5	0.278	66	1
760	2	88	58.000000	26	16	28.4	0.766	22	0
761	9	170	74.000000	31	0	44.0	0.403	43	1
762	9	89	62.000000	0	0	22.5	0.142	33	0
763	10	101	76.000000	48	180	32.9	0.171	63	0
764	2	122	70.000000	27	0	36.8	0.340	27	0
765	5	121	72.000000	23	112	26.2	0.245	30	0
766	1	126	60.000000	0	0	30.1	0.349	47	1
767	1	93	70.000000	31	0	30.4	0.315	23	0

```
x = df["BloodPressure"].median()
```

```
df["BloodPressure"].fillna(x, inplace = True)
print(df.to_string())
```

69	4	146	85.000000	27	100	28.9	0.189	27	0
70	2	100	66.000000	20	90	32.9	0.867	28	1
71	5	139	64.000000	35	140	28.6	0.411	26	0
72	13	126	90.000000	0	0	43.4	0.583	42	1
73	4	129	86.000000	20	270	35.1	0.231	23	0
74	1	79	75.000000	30	0	32.0	0.396	22	0
75	1	0	48.000000	20	0	24.7	0.140	22	0
76	7	62	78.000000	0	0	32.6	0.391	41	0
77	5	95	72.000000	33	0	37.7	0.370	27	0
78	0	131	69.549202	0	0	43.2	0.270	26	1
79	2	112	66.000000	22	0	25.0	0.307	24	0
80	3	113	44.000000	13	0	22.4	0.140	22	0
81	2	74	0.000000	0	0	0.0	0.102	22	0
82	7	83	78.000000	26	71	29.3	0.767	36	0
83	0	101	65.000000	28	0	24.6	0.237	22	0
84	5	137	108.000000	0	0	48.8	0.227	37	1
85	2	110	74.000000	29	125	32.4	0.698	27	0
86	13	106	72.000000	54	0	36.6	0.178	45	0
87	2	100	68.000000	25	71	38.5	0.324	26	0
88	15	136	70.000000	32	110	37.1	0.153	43	1
89	1	107	68.000000	19	0	26.5	0.165	24	0
90	1	80	55.000000	0	0	19.1	0.258	21	0
91	4	123	80.000000	15	176	32.0	0.443	34	0
92	7	81	78.000000	40	48	46.7	0.261	42	0
93	4	134	72.000000	0	0	23.8	0.277	60	1
94	2	142	82.000000	18	64	24.7	0.761	21	0
95	6	144	72.000000	27	228	33.9	0.255	40	0
96	2	92	62.000000	28	0	31.6	0.130	24	0
97	1	71	48.000000	18	76	20.4	0.323	22	0
98	6	93	50.000000	30	64	28.7	0.356	23	0
99	1	122	90.000000	51	220	49.7	0.325	31	1
100	1	163	72.000000	0	0	39.0	1.222	33	1
101	1	151	60.000000	0	0	26.1	0.179	22	0
102	0	125	96.000000	0	0	22.5	0.262	21	0
103	1	81	72.000000	18	40	26.6	0.283	24	0
104	2	85	65.000000	0	0	39.6	0.930	27	0
105	1	126	56.000000	29	152	28.7	0.801	21	0
106	1	96	122.000000	0	0	22.4	0.207	27	0
107	4	144	58.000000	28	140	29.5	0.287	37	0
108	3	83	58.000000	31	18	34.3	0.336	25	0
109	0	95	85.000000	25	36	37.4	0.247	24	1
110	2	171	72.000000	22	125	22.2	0.100	24	1

```
import pandas as pd

df = pd.read_csv('diabetes.csv')

x = df["BloodPressure"].mode()

df["BloodPressure"].fillna(x, inplace = True)

df.loc[7, 'Duration'] = 45
print(df.to_string())
```

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedigreeFunction	Age	Outcome	Duration
0	6	148	72.0	35	0	33.6	0.627	50	1	NaN
1	1	85	66.0	29	0	26.6	0.351	31	0	NaN
2	8	183	64.0	0	0	23.3	0.672	32	1	NaN
3	1	89	66.0	23	94	28.1	0.167	21	0	NaN
4	0	137	40.0	35	168	43.1	2.288	33	1	NaN
5	5	116	74.0	0	0	25.6	0.201	30	0	NaN
6	3	78	50.0	32	88	31.0	0.248	26	1	NaN
7	10	115	NaN	0	0	35.3	0.134	29	0	45.0
8	2	197	70.0	45	543	30.5	0.158	53	1	NaN
9	8	125	96.0	0	0	0.0	0.232	54	1	NaN
10	4	110	92.0	0	0	37.6	0.191	30	0	NaN
11	10	168	74.0	0	0	38.0	0.537	34	1	NaN
12	10	139	80.0	0	0	27.1	1.441	57	0	NaN
13	1	189	60.0	23	846	30.1	0.398	59	1	NaN
14	5	166	72.0	19	175	25.8	0.587	51	1	NaN
15	7	100	NaN	0	0	30.0	0.484	32	1	NaN
16	0	118	84.0	47	230	45.8	0.551	31	1	NaN
17	7	107	74.0	0	0	29.6	0.254	31	1	NaN
18	1	103	30.0	38	83	43.3	0.183	33	0	NaN
19	1	115	70.0	30	96	34.6	0.529	32	1	NaN
20	3	126	88.0	41	235	39.3	0.704	27	0	NaN
21	8	99	NaN	0	0	35.4	0.388	50	0	NaN
22	7	196	90.0	0	0	39.8	0.451	41	1	NaN
23	9	119	80.0	35	0	29.0	0.263	29	1	NaN
24	11	143	94.0	33	146	36.6	0.254	51	1	NaN
25	10	125	70.0	26	115	31.1	0.205	41	1	NaN
26	7	147	76.0	0	0	39.4	0.257	43	1	NaN
27	1	97	66.0	15	140	23.2	0.487	22	0	NaN
28	13	145	82.0	19	110	22.2	0.245	57	0	NaN
29	5	117	92.0	0	0	34.1	0.337	38	0	NaN
30	5	109	75.0	26	0	36.0	0.546	60	0	NaN
31	3	158	76.0	36	245	31.6	0.851	28	1	NaN
32	3	88	58.0	11	54	24.8	0.267	22	0	NaN
33	6	92	92.0	0	0	19.9	0.188	28	0	NaN

34	10	122	78.0	31	0	27.6	0.512	45	0	NaN
35	4	103	60.0	33	192	24.0	0.966	33	0	NaN
36	11	138	76.0	0	0	33.2	0.420	35	0	NaN
37	9	102	NaN	37	0	32.9	0.665	46	1	NaN
38	2	90	68.0	42	0	38.2	0.503	27	1	NaN
39	4	111	72.0	47	207	37.1	1.390	56	1	NaN
40	3	180	64.0	25	70	34.0	0.271	26	0	NaN
41	7	133	84.0	0	0	40.2	0.696	37	0	NaN
42	7	106	92.0	18	0	22.7	0.235	48	0	NaN
43	9	171	110.0	24	240	45.4	0.721	54	1	NaN
44	7	159	64.0	0	0	27.4	0.294	40	0	NaN
45	0	180	66.0	39	0	42.0	1.893	25	1	NaN
46	1	146	56.0	0	0	29.7	0.564	29	0	NaN
47	2	71	70.0	27	0	28.0	0.586	22	0	NaN
48	7	103	66.0	32	0	39.1	0.344	31	1	NaN
49	7	105	0.0	0	0	0.0	0.305	24	0	NaN
50	1	103	80.0	11	82	19.4	0.491	22	0	NaN
51	1	101	50.0	15	36	24.2	0.526	26	0	NaN
52	5	88	66.0	21	23	24.4	0.342	30	0	NaN
53	8	176	90.0	34	300	33.7	0.467	58	1	NaN
54	7	150	66.0	42	342	34.7	0.718	42	0	NaN
55	1	73	50.0	10	0	23.0	0.248	21	0	NaN
56	7	187	68.0	39	304	37.7	0.254	41	1	NaN

```
for x in df.index:
    if df.loc[x, "Duration"] > 120:
        df.loc[x, "Duration"] = 120
```

```
for x in df.index:
    if df.loc[x, "Duration"] > 120:
        df.drop(x, inplace = True)
print(df.to_string())
```

```
print(df.duplicated())
```

0	False
1	False
2	False
3	False
4	False
...	
763	False
764	False
765	False
766	False
767	False
Length: 768, dtype: bool	

```
df.drop_duplicates(inplace = True)
```

```
print(df.to_string())
```

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedigreeFunction	Age	Outcome	Duration
0	6	148	72.0	35	0	33.6	0.627	50	1	NaN
1	1	85	66.0	29	0	26.6	0.351	31	0	NaN
2	8	183	64.0	0	0	23.3	0.672	32	1	NaN
3	1	89	66.0	23	94	28.1	0.167	21	0	NaN
4	0	137	40.0	35	168	43.1	2.288	33	1	NaN
5	5	116	74.0	0	0	25.6	0.201	30	0	NaN
6	3	78	50.0	32	88	31.0	0.248	26	1	NaN
7	10	115	NaN	0	0	35.3	0.134	29	0	45.0
8	2	197	70.0	45	543	30.5	0.158	53	1	NaN
9	8	125	96.0	0	0	0.0	0.232	54	1	NaN
10	4	110	92.0	0	0	37.6	0.191	30	0	NaN
11	10	168	74.0	0	0	38.0	0.537	34	1	NaN
12	10	139	80.0	0	0	27.1	1.441	57	0	NaN
13	1	189	60.0	23	846	30.1	0.398	59	1	NaN
14	5	166	72.0	19	175	25.8	0.587	51	1	NaN
15	7	100	NaN	0	0	30.0	0.484	32	1	NaN
16	0	118	84.0	47	230	45.8	0.551	31	1	NaN
17	7	107	74.0	0	0	29.6	0.254	31	1	NaN
18	1	103	30.0	38	83	43.3	0.183	33	0	NaN
19	1	115	70.0	30	96	34.6	0.529	32	1	NaN
20	3	126	88.0	41	235	39.3	0.704	27	0	NaN
21	8	99	NaN	0	0	35.4	0.388	50	0	NaN
22	7	196	90.0	0	0	39.8	0.451	41	1	NaN
23	9	119	80.0	35	0	29.0	0.263	29	1	NaN
24	11	143	94.0	33	146	36.6	0.254	51	1	NaN
25	10	125	70.0	26	115	31.1	0.205	41	1	NaN
26	7	147	76.0	0	0	39.4	0.257	43	1	NaN
27	1	97	66.0	15	140	23.2	0.487	22	0	NaN
28	13	145	82.0	19	110	22.2	0.245	57	0	NaN
29	5	117	92.0	0	0	34.1	0.337	38	0	NaN
30	5	109	75.0	26	0	36.0	0.546	60	0	NaN
31	3	158	76.0	36	245	31.6	0.851	28	1	NaN
32	3	88	58.0	11	54	24.8	0.267	22	0	NaN

33	6	92	92.0	0	0	19.9	0.188	28	0	NaN
34	10	122	78.0	31	0	27.6	0.512	45	0	NaN
35	4	103	60.0	33	192	24.0	0.966	33	0	NaN
36	11	138	76.0	0	0	33.2	0.420	35	0	NaN
37	9	102	NaN	37	0	32.9	0.665	46	1	NaN
38	2	90	68.0	42	0	38.2	0.503	27	1	NaN
39	4	111	72.0	47	207	37.1	1.390	56	1	NaN
40	3	180	64.0	25	70	34.0	0.271	26	0	NaN
41	7	133	84.0	0	0	40.2	0.696	37	0	NaN
42	7	106	92.0	18	0	22.7	0.235	48	0	NaN
43	9	171	110.0	24	240	45.4	0.721	54	1	NaN
44	7	159	64.0	0	0	27.4	0.294	40	0	NaN
45	0	180	66.0	39	0	42.0	1.893	25	1	NaN
46	1	146	56.0	0	0	29.7	0.564	29	0	NaN
47	2	71	70.0	27	0	28.0	0.586	22	0	NaN
48	7	103	66.0	32	0	39.1	0.344	31	1	NaN
49	7	105	0.0	0	0	0.0	0.305	24	0	NaN
50	1	103	80.0	11	82	19.4	0.491	22	0	NaN
51	1	101	50.0	15	36	24.2	0.526	26	0	NaN
52	5	88	66.0	21	23	24.4	0.342	30	0	NaN
53	8	176	90.0	34	300	33.7	0.467	58	1	NaN
54	7	150	66.0	42	342	34.7	0.718	42	0	NaN
55	1	73	50.0	10	0	23.0	0.248	21	0	NaN
56	7	187	68.0	39	304	37.7	0.254	41	1	NaN

```
# drop the "Cabin" column from the dataframe
titanic_data = titanic_data.drop(columns='Duration', axis=1)
```

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Conclusion:

Data cleaning, integration, and transformation are essential steps in preparing Electronic Healthcare Records (EHR) data for analysis. By addressing issues such as duplicates, errors, missing data, and irrelevant content, researchers and healthcare professionals can ensure the accuracy and quality of the data, which in turn supports reliable healthcare analytics, decision-making, and research outcomes. Properly cleaned and standardized EHR data is a fundamental requirement for any meaningful analysis or research in the healthcare domain.



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