

# INTRODUCTION

According to the World Health Organization (WHO), diabetes is a chronic, metabolic disease characterized by elevated levels of blood glucose (or blood sugar), which leads over time to serious damage to the heart, blood vessels, eyes, kidneys and nerves. The most common is type 2 diabetes, usually in adults, which occurs when the body becomes resistant to insulin or doesn't make enough insulin. About 422 million people worldwide have diabetes, the majority living in low-and middle-income countries, and 1.5 million deaths are directly attributed to diabetes each year. Both the number of cases and the prevalence of diabetes have been steadily increasing over the past few decades.

## Objective of study

This study aims to predict if certain patients have diabetes or not using a machine learning model built with support vector machine. The model was trained and tested using a PIMA Diabetes dataset. Certain risk factors and its relation to diabetes was also observed and visualized to better show its relationship with the condition.

## Data Processing

Importing the Dependencies

```
In [1]: import numpy as np
import pandas as pd
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split
from sklearn import svm
from sklearn.metrics import accuracy_score
```

Data Collection and Analysis

PIMA Diabetes Dataset

```
In [2]: # loading the diabetes dataset to a pandas DataFrame
diabetes_dataset = pd.read_csv('diabetes.csv')
```

```
In [3]: pd.read_csv?
```

**Signature:**

```
pd.read_csv(
    filepath_or_buffer: 'FilePath | ReadCsvBuffer[bytes] | ReadCsvBuffer[str]',
    *,
    sep: 'str | None | lib.NoDefault' = <no_default>,
    delimiter: 'str | None | lib.NoDefault' = None,
    header: 'int | Sequence[int] | None | Literal["infer"]' = 'infer',
    names: 'Sequence[Hashable] | None | lib.NoDefault' = <no_default>,
    index_col: 'IndexLabel | Literal[False] | None' = None,
    usecols: 'UsecolsArgType' = None,
    dtype: 'DtypeArg | None' = None,
    engine: 'CSVEngine | None' = None,
    converters: 'Mapping[Hashable, Callable] | None' = None,
    true_values: 'list | None' = None,
    false_values: 'list | None' = None,
    skipinitialspace: 'bool' = False,
    skiprows: 'list[int] | int | Callable[[Hashable], bool] | None' = None,
    skipfooter: 'int' = 0,
    nrows: 'int | None' = None,
    na_values: 'Hashable | Iterable[Hashable] | Mapping[Hashable, Iterable[Hashable]] | None' = None,
    keep_default_na: 'bool' = True,
    na_filter: 'bool' = True,
    verbose: 'bool | lib.NoDefault' = <no_default>,
    skip_blank_lines: 'bool' = True,
    parse_dates: 'bool | Sequence[Hashable] | None' = None,
    infer_datetime_format: 'bool | lib.NoDefault' = <no_default>,
    keep_date_col: 'bool | lib.NoDefault' = <no_default>,
    date_parser: 'Callable | lib.NoDefault' = <no_default>,
    date_format: 'str | dict[Hashable, str] | None' = None,
    dayfirst: 'bool' = False,
    cache_dates: 'bool' = True,
    iterator: 'bool' = False,
    chunksize: 'int | None' = None,
    compression: 'CompressionOptions' = 'infer',
    thousands: 'str | None' = None,
    decimal: 'str' = '.',
    lineterminator: 'str | None' = None,
```

```

quotechar: 'str' = '"',
quoting: 'int' = 0,
doublequote: 'bool' = True,
escapechar: 'str | None' = None,
comment: 'str | None' = None,
encoding: 'str | None' = None,
encoding_errors: 'str | None' = 'strict',
dialect: 'str | csv.Dialect | None' = None,
on_bad_lines: 'str' = 'error',
delim_whitespace: 'bool | lib.NoDefault' = <no_default>,
low_memory: 'bool' = True,
memory_map: 'bool' = False,
float_precision: "Literal['high', 'legacy'] | None" = None,
storage_options: 'StorageOptions | None' = None,
dtype_backend: 'DtypeBackend | lib.NoDefault' = <no_default>,
) -> 'DataFrame | TextFileReader'

```

#### Docstring:

Read a comma-separated values (csv) file into DataFrame.

Also supports optionally iterating or breaking of the file into chunks.

Additional help can be found in the online docs for

`IO Tools` <[https://pandas.pydata.org/pandas-docs/stable/user\\_guide/io.html](https://pandas.pydata.org/pandas-docs/stable/user_guide/io.html)>`\_.

#### Parameters

-----

`filepath_or_buffer` : str, path object or file-like object

Any valid string path is acceptable. The string could be a URL. Valid URL schemes include http, ftp, s3, gs, and file. For file URLs, a host is expected. A local file could be: `file://localhost/path/to/table.csv`.

If you want to pass in a path object, pandas accepts any `os.PathLike`.

By file-like object, we refer to objects with a `read()` method, such as a file handle (e.g. via builtin `open` function) or `StringIO`.

`sep` : str, default ','

Character or regex pattern to treat as the delimiter. If `sep=None`, the C engine cannot automatically detect

the separator, but the Python parsing engine can, meaning the latter will be used and automatically detect the separator from only the first valid row of the file by Python's builtin sniffer tool, `csv.Sniffer`.

In addition, separators longer than 1 character and different from `\"\\s+\"` will be interpreted as regular expressions and will also force the use of the Python parsing engine. Note that regex delimiters are prone to ignoring quoted data. Regex example: `\"\\r\\t\"`.

`delimiter` : str, optional

Alias for `sep`.

`header` : int, Sequence of int, 'infer' or None, default 'infer'

Row number(s) containing column labels and marking the start of the data (zero-indexed). Default behavior is to infer the column names: if no `names` are passed the behavior is identical to `header=0` and column names are inferred from the first line of the file, if column names are passed explicitly to `names` then the behavior is identical to `header=None`. Explicitly pass `header=0` to be able to replace existing names. The header can be a list of integers that specify row locations for a `:class:`~pandas.MultiIndex`` on the columns e.g. `[0, 1, 3]`. Intervening rows that are not specified will be skipped (e.g. 2 in this example is skipped). Note that this parameter ignores commented lines and empty lines if `skip_blank_lines=True`, so `header=0` denotes the first line of data rather than the first line of the file.

`names` : Sequence of Hashable, optional

Sequence of column labels to apply. If the file contains a header row, then you should explicitly pass `header=0` to override the column names. Duplicates in this list are not allowed.

`index_col` : Hashable, Sequence of Hashable or False, optional

Column(s) to use as row label(s), denoted either by column labels or column indices. If a sequence of labels or indices is given, `:class:`~pandas.MultiIndex`` will be formed for the row labels.

Note: `index_col=False` can be used to force pandas to *not* use the first column as the index, e.g., when you have a malformed file with delimiters at the end of each line.

`usecols` : Sequence of Hashable or Callable, optional

Subset of columns to select, denoted either by column labels or column indices. If list-like, all elements must either

be positional (i.e. integer indices into the document columns) or strings that correspond to column names provided either by the user in `names` or inferred from the document header row(s). If `names` are given, the document header row(s) are not taken into account. For example, a valid list-like `usecols` parameter would be `[0, 1, 2]` or `['foo', 'bar', 'baz']`. Element order is ignored, so `usecols=[0, 1]` is the same as `[1, 0]`.

To instantiate a `pandas.DataFrame` from `data` with element order preserved use `pd.read_csv(data, usecols=['foo', 'bar'])[['foo', 'bar']]` for columns in `['foo', 'bar']` order or `pd.read_csv(data, usecols=['foo', 'bar'])[['bar', 'foo']]` for `['bar', 'foo']` order.

If callable, the callable function will be evaluated against the column names, returning names where the callable function evaluates to `True`. An example of a valid callable argument would be `lambda x: x.upper()` in `['AAA', 'BBB', 'DDD']`. Using this parameter results in much faster parsing time and lower memory usage.

`dtype` : dtype or dict of {Hashable : dtype}, optional  
Data type(s) to apply to either the whole dataset or individual columns. E.g., `{a: np.float64, b: np.int32, c: 'Int64'}`. Use `str` or `object` together with suitable `na_values` settings to preserve and not interpret `dtype`. If `converters` are specified, they will be applied INSTEAD of `dtype` conversion.

.. versionadded:: 1.5.0

Support for `defaultdict` was added. Specify a `defaultdict` as input where the default determines the `dtype` of the columns which are not explicitly listed.

`engine` : {'c', 'python', 'pyarrow'}, optional  
Parser engine to use. The C and pyarrow engines are faster, while the python engine is currently more feature-complete. Multithreading is currently only supported by the pyarrow engine.

.. versionadded:: 1.4.0

The 'pyarrow' engine was added as an \*experimental\* engine, and some features are unsupported, or may not work correctly, with this engine.

`converters` : dict of {Hashable : Callable}, optional  
Functions for converting values in specified columns. Keys can either be column labels or column indices.  
`true_values` : list, optional  
Values to consider as `True` in addition to case-insensitive variants of 'True'.  
`false_values` : list, optional  
Values to consider as `False` in addition to case-insensitive variants of 'False'.  
`skipinitialspace` : bool, default False  
Skip spaces after delimiter.  
`skiprows` : int, list of int or Callable, optional  
Line numbers to skip (0-indexed) or number of lines to skip (`int`) at the start of the file.

If callable, the callable function will be evaluated against the row indices, returning `True` if the row should be skipped and `False` otherwise. An example of a valid callable argument would be `lambda x: x in [0, 2]`.

`skipfooter` : int, default 0  
Number of lines at bottom of file to skip (Unsupported with `engine='c'`).  
`nrows` : int, optional  
Number of rows of file to read. Useful for reading pieces of large files.  
`na_values` : Hashable, Iterable of Hashable or dict of {Hashable : Iterable}, optional  
Additional strings to recognize as `NA`/`NaN`. If `dict` passed, specific per-column `NA` values. By default the following values are interpreted as `NaN`: " ", "#N/A", "#N/A N/A", "#NA", "-1.#IND", "-1.#QNAN", "-NaN", "-nan", "1.#IND", "1.#QNAN", "<NA>", "N/A", "NA", "NULL", "NaN", "None", "n/a", "nan", "null".

`keep_default_na` : bool, default True  
Whether or not to include the default `NaN` values when parsing the data. Depending on whether `na_values` is passed in, the behavior is as follows:

- \* If `keep_default_na` is `True`, and `na_values` are specified, `na_values` is appended to the default `NaN` values used for parsing.
- \* If `keep_default_na` is `True`, and `na_values` are not specified, only the default `NaN` values are used for parsing.
- \* If `keep_default_na` is `False`, and `na_values` are specified, only the `NaN` values specified `na_values` are used for parsing.
- \* If `keep_default_na` is `False`, and `na_values` are not specified, no strings will be parsed as `NaN`.

Note that if `na_filter` is passed in as `False`, the `keep_default_na` and `na_values` parameters will be ignored.

`na_filter` : bool, default True  
Detect missing value markers (empty strings and the value of `na_values`). In data without any `NA` values, passing `na_filter=False` can improve the performance of reading a large file.  
`verbose` : bool, default False  
Indicate number of `NA` values placed in non-numeric columns.

.. deprecated:: 2.2.0

`skip_blank_lines` : bool, default True  
If ``True``, skip over blank lines rather than interpreting as ``NaN`` values.  
`parse_dates` : bool, list of Hashable, list of lists or dict of {Hashable : list}, default False  
The behavior is as follows:

- \* ``bool``. If ``True`` -> try parsing the index. Note: Automatically set to ``True`` if ``date\_format`` or ``date\_parser`` arguments have been passed.
- \* ``list`` of ``int`` or names. e.g. If ``[1, 2, 3]`` -> try parsing columns 1, 2, 3 each as a separate date column.
- \* ``list`` of ``list``. e.g. If ``[[1, 3]]`` -> combine columns 1 and 3 and parse as a single date column. Values are joined with a space before parsing.
- \* ``dict``, e.g. ``{'foo' : [1, 3]}`` -> parse columns 1, 3 as date and call result 'foo'. Values are joined with a space before parsing.

If a column or index cannot be represented as an array of ``datetime``, say because of an unparseable value or a mixture of timezones, the column or index will be returned unaltered as an ``object`` data type. For non-standard ``datetime`` parsing, use `:func:`~pandas.to_datetime`` after `:func:`~pandas.read_csv``.

Note: A fast-path exists for iso8601-formatted dates.

`infer_datetime_format` : bool, default False

If ``True`` and ``parse\_dates`` is enabled, pandas will attempt to infer the format of the ``datetime`` strings in the columns, and if it can be inferred, switch to a faster method of parsing them. In some cases this can increase the parsing speed by 5-10x.

.. deprecated:: 2.0.0

A strict version of this argument is now the default, passing it has no effect.

`keep_date_col` : bool, default False

If ``True`` and ``parse\_dates`` specifies combining multiple columns then keep the original columns.

`date_parser` : Callable, optional

Function to use for converting a sequence of string columns to an array of ``datetime`` instances. The default uses ``dateutil.parser.parser`` to do the conversion. pandas will try to call ``date\_parser`` in three different ways, advancing to the next if an exception occurs: 1) Pass one or more arrays (as defined by ``parse\_dates``) as arguments; 2) concatenate (row-wise) the string values from the columns defined by ``parse\_dates`` into a single array and pass that; and 3) call ``date\_parser`` once for each row using one or more strings (corresponding to the columns defined by ``parse\_dates``) as arguments.

.. deprecated:: 2.0.0

Use ``date_format`` instead, or read in as ``object`` and then apply `:func:`~pandas.to_datetime`` as-needed.

`date_format` : str or dict of column -> format, optional

Format to use for parsing dates when used in conjunction with ``parse\_dates``. The strftime to parse time, e.g. `:const: "%d/%m/%Y"`. See

``strftime`` documentation

<<https://docs.python.org/3/library/datetime.html>

`#strftime-and-strptime-behavior`` for more information on choices, though note that `:const: "%f"` will parse all the way up to nanoseconds.

You can also pass:

- "ISO8601", to parse any `ISO8601` <[https://en.wikipedia.org/wiki/ISO\\_8601](https://en.wikipedia.org/wiki/ISO_8601)>`\_ time string (not necessarily in exactly the same format);
- "mixed", to infer the format for each element individually. This is risky, and you should probably use it along with ``dayfirst``.

.. versionadded:: 2.0.0

`dayfirst` : bool, default False

DD/MM format dates, international and European format.

`cache_dates` : bool, default True

If ``True``, use a cache of unique, converted dates to apply the ``datetime`` conversion. May produce significant speed-up when parsing duplicate date strings, especially ones with timezone offsets.

`iterator` : bool, default False

Return ``TextFileReader`` object for iteration or getting chunks with ``get_chunk()``.

`chunksize` : int, optional

Number of lines to read from the file per chunk. Passing a value will cause the function to return a ``TextFileReader`` object for iteration.

See the `IO Tools docs`

<<https://pandas.pydata.org/pandas-docs/stable/io.html#io-chunking>>`\_ for more information on ``iterator`` and ``chunksize``.

`compression` : str or dict, default 'infer'

For on-the-fly decompression of on-disk data. If 'infer' and 'filepath\_or\_buffer' is path-like, then detect compression from the following extensions: '.gz', '.bz2', '.zip', '.xz', '.zst', '.tar', '.tar.gz', '.tar.xz' or '.tar.bz2'

```

(otherwise no compression).
If using 'zip' or 'tar', the ZIP file must contain only one data file to be read in.
Set to ``None`` for no decompression.
Can also be a dict with key ``'method'`` set
to one of {'zip', 'gzip', 'bz2', 'zstd', 'xz', 'tar'} and
other key-value pairs are forwarded to
``zipfile.ZipFile``, ``gzip.GzipFile``,
``bz2.BZ2File``, ``zstandard.ZstdDecompressor``, ``lzma.LZMAFile`` or
``tarfile.TarFile``, respectively.
As an example, the following could be passed for Zstandard decompression using a
custom compression dictionary:
``compression={'method': 'zstd', 'dict_data': my_compression_dict}``.

.. versionadded:: 1.5.0
    Added support for ``.tar`` files.

.. versionchanged:: 1.4.0 Zstandard support.

thousands : str (length 1), optional
    Character acting as the thousands separator in numerical values.
decimal : str (length 1), default '.'
    Character to recognize as decimal point (e.g., use ',' for European data).
lineterminator : str (length 1), optional
    Character used to denote a line break. Only valid with C parser.
quotechar : str (length 1), optional
    Character used to denote the start and end of a quoted item. Quoted
    items can include the ``delimiter`` and it will be ignored.
quoting : {0 or csv.QUOTE_MINIMAL, 1 or csv.QUOTE_ALL, 2 or csv.QUOTE_NONNUMERIC, 3 or csv.QUOTE_NONE}, default
csv.QUOTE_MINIMAL
    Control field quoting behavior per ``csv.QUOTE_*`` constants. Default is
    ``csv.QUOTE_MINIMAL`` (i.e., 0) which implies that only fields containing special
    characters are quoted (e.g., characters defined in ``quotechar``, ``delimiter``,
    or ``lineterminator``).
doublequote : bool, default True
    When ``quotechar`` is specified and ``quoting`` is not ``QUOTE_NONE``, indicate
    whether or not to interpret two consecutive ``quotechar`` elements INSIDE a
    field as a single ``quotechar`` element.
escapechar : str (length 1), optional
    Character used to escape other characters.
comment : str (length 1), optional
    Character indicating that the remainder of line should not be parsed.
    If found at the beginning
    of a line, the line will be ignored altogether. This parameter must be a
    single character. Like empty lines (as long as ``skip_blank_lines=True``),
    fully commented lines are ignored by the parameter ``header`` but not by
    ``skiprows``. For example, if ``comment='#'``, parsing
    ``#empty\na,b,c\n1,2,3`` with ``header=0`` will result in ``a,b,c`` being
    treated as the header.
encoding : str, optional, default 'utf-8'
    Encoding to use for UTF when reading/writing (ex. ``'utf-8'``). `List of Python
    standard encodings
    <https://docs.python.org/3/library/codecs.html#standard-encodings>`_ .

encoding_errors : str, optional, default 'strict'
    How encoding errors are treated. `List of possible values
    <https://docs.python.org/3/library/codecs.html#error-handlers>`_ .

.. versionadded:: 1.3.0

dialect : str or csv.Dialect, optional
    If provided, this parameter will override values (default or not) for the
    following parameters: ``delimiter``, ``doublequote``, ``escapechar``,
    ``skipinitialspace``, ``quotechar``, and ``quoting``. If it is necessary to
    override values, a ``ParserWarning`` will be issued. See ``csv.Dialect``
    documentation for more details.
on_bad_lines : {'error', 'warn', 'skip'} or Callable, default 'error'
    Specifies what to do upon encountering a bad line (a line with too many fields).
    Allowed values are :

    - ``'error'``, raise an Exception when a bad line is encountered.
    - ``'warn'``, raise a warning when a bad line is encountered and skip that line.
    - ``'skip'``, skip bad lines without raising or warning when they are encountered.

.. versionadded:: 1.3.0

.. versionadded:: 1.4.0

    - Callable, function with signature
      ``(bad_line: list[str]) -> list[str] | None`` that will process a single
      bad line. ``bad_line`` is a list of strings split by the ``sep``.
      If the function returns ``None``, the bad line will be ignored.
      If the function returns a new ``list`` of strings with more elements than
      expected, a ``ParserWarning`` will be emitted while dropping extra elements.

```

Only supported when ``engine='python'``

.. versionchanged:: 2.2.0

- Callable, function with signature as described in `pyarrow documentation`\_ <[https://arrow.apache.org/docs/python/generated/pyarrow.csv.ParseOptions.html#pyarrow.csv.ParseOptions.invalid\\_row\\_handler](https://arrow.apache.org/docs/python/generated/pyarrow.csv.ParseOptions.html#pyarrow.csv.ParseOptions.invalid_row_handler)>`\_ when ``engine='pyarrow'``

delim\_whitespace : bool, default False

Specifies whether or not whitespace (e.g. ``' '`` or ``'\t'``) will be used as the ``sep`` delimiter. Equivalent to setting ``sep='\s+'``. If this option is set to ``True``, nothing should be passed in for the ``delimiter`` parameter.

.. deprecated:: 2.2.0

Use ``sep="\s+"`` instead.

low\_memory : bool, default True

Internally process the file in chunks, resulting in lower memory use while parsing, but possibly mixed type inference. To ensure no mixed types either set ``False``, or specify the type with the ``dtype`` parameter. Note that the entire file is read into a single :class:`~pandas.DataFrame` regardless, use the ``chunksize`` or ``iterator`` parameter to return the data in chunks. (Only valid with C parser).

memory\_map : bool, default False

If a filepath is provided for ``filepath\_or\_buffer``, map the file object directly onto memory and access the data directly from there. Using this option can improve performance because there is no longer any I/O overhead.

float\_precision : {'high', 'legacy', 'round\_trip'}, optional

Specifies which converter the C engine should use for floating-point values. The options are ``None`` or ``'high'`` for the ordinary converter, ``'legacy'`` for the original lower precision pandas converter, and ``'round\_trip'`` for the round-trip converter.

storage\_options : dict, optional

Extra options that make sense for a particular storage connection, e.g. host, port, username, password, etc. For HTTP(S) URLs the key-value pairs are forwarded to ``urllib.request.Request`` as header options. For other URLs (e.g. starting with "s3://", and "gcs://") the key-value pairs are forwarded to ``fsspec.open``. Please see ``fsspec`` and ``urllib`` for more details, and for more examples on storage options refer [here](https://pandas.pydata.org/docs/user_guide/io.html?highlight=storage_options#reading-writing-remote-files) <[https://pandas.pydata.org/docs/user\\_guide/io.html?highlight=storage\\_options#reading-writing-remote-files](https://pandas.pydata.org/docs/user_guide/io.html?highlight=storage_options#reading-writing-remote-files)>`\_.

dtype\_backend : {'numpy\_nullable', 'pyarrow'}, default 'numpy\_nullable'

Back-end data type applied to the resultant :class:`DataFrame` (still experimental). Behaviour is as follows:

- \* ``"numpy\_nullable"``: returns nullable-dtype-backed :class:`DataFrame` (default).
- \* ``"pyarrow"``: returns pyarrow-backed nullable :class:`ArrowDtype` DataFrame.

.. versionadded:: 2.0

## Returns

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### DataFrame or TextFileReader

A comma-separated values (csv) file is returned as two-dimensional data structure with labeled axes.

## See Also

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DataFrame.to\_csv : Write DataFrame to a comma-separated values (csv) file.

read\_table : Read general delimited file into DataFrame.

read\_fwf : Read a table of fixed-width formatted lines into DataFrame.

## Examples

-----

```
>>> pd.read_csv('data.csv') # doctest: +SKIP
```

**File:** c:\users\hp\anaconda3\lib\site-packages\pandas\io\parsers\readers.py

**Type:** function

```
In [4]: # printing the first 5 rows of the dataset
diabetes_dataset.head()
```

Out[4]:

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedigreeFunction	Age	Outcome
0	6	148	72	35	0	33.6	0.627	50	1
1	1	85	66	29	0	26.6	0.351	31	0
2	8	183	64	0	0	23.3	0.672	32	1
3	1	89	66	23	94	28.1	0.167	21	0
4	0	137	40	35	168	43.1	2.288	33	1

In [5]: `# number of rows and Columns in this dataset`  
`diabetes_dataset.shape`

Out[5]: (768, 9)

In [6]: `# getting the statistical measures of the data`  
`diabetes_dataset.describe()`

Out[6]:

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedigreeFunction	Age	C
count	768.000000	768.000000	768.000000	768.000000	768.000000	768.000000	768.000000	768.000000	768.000000
mean	3.845052	120.894531	69.105469	20.536458	79.799479	31.992578	0.471876	33.240885	0.350222
std	3.369578	31.972618	19.355807	15.952218	115.244002	7.884160	0.331329	11.760232	0.476043
min	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.078000	21.000000	0.000000
25%	1.000000	99.000000	62.000000	0.000000	0.000000	27.300000	0.243750	24.000000	0.000000
50%	3.000000	117.000000	72.000000	23.000000	30.500000	32.000000	0.372500	29.000000	0.000000
75%	6.000000	140.250000	80.000000	32.000000	127.250000	36.600000	0.626250	41.000000	1.000000
max	17.000000	199.000000	122.000000	99.000000	846.000000	67.100000	2.420000	81.000000	1.000000

In [7]: `diabetes_dataset['Outcome'].value_counts()`

Out[7]: Outcome  
0 500  
1 268  
Name: count, dtype: int64  
  
0 --> Non-Diabetic  
  
1 --> Diabetic

In [8]: `diabetes_dataset.groupby('Outcome').mean()`

Out[8]:

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedigreeFunction	Age
Outcome								
0	3.298000	109.980000	68.184000	19.664000	68.792000	30.304200	0.429734	31.190000
1	4.865672	141.257463	70.824627	22.164179	100.335821	35.142537	0.550500	37.067164

In [9]: `# separating the data and labels`  
`X = diabetes_dataset.drop(columns = 'Outcome', axis=1)`  
`Y = diabetes_dataset['Outcome']`

In [10]: `print(X)`

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	\
0	6	148	72	35	0	33.6	
1	1	85	66	29	0	26.6	
2	8	183	64	0	0	23.3	
3	1	89	66	23	94	28.1	
4	0	137	40	35	168	43.1	
..	...	...	...	...	...	...	
763	10	101	76	48	180	32.9	
764	2	122	70	27	0	36.8	
765	5	121	72	23	112	26.2	
766	1	126	60	0	0	30.1	
767	1	93	70	31	0	30.4	

	DiabetesPedigreeFunction	Age
0	0.627	50
1	0.351	31
2	0.672	32
3	0.167	21
4	2.288	33
..	...	...
763	0.171	63
764	0.340	27
765	0.245	30
766	0.349	47
767	0.315	23

[768 rows x 8 columns]

In [11]: `print(Y)`

```
0      1
1      0
2      1
3      0
4      1
..
763    0
764    0
765    0
766    1
767    0
```

Name: Outcome, Length: 768, dtype: int64

Data Standardization

In [12]: `scaler = StandardScaler()`

In [13]: `scaler.fit(X)`

Out[13]: `StandardScaler` ⓘ ⓘ  
`StandardScaler()`

In [14]: `standardized_data = scaler.transform(X)`

In [15]: `print(standardized_data)`

```
[[ 0.63994726  0.84832379  0.14964075 ...  0.20401277  0.46849198
   1.4259954 ]
 [-0.84488505 -1.12339636 -0.16054575 ... -0.68442195 -0.36506078
  -0.19067191]
 [ 1.23388019  1.94372388 -0.26394125 ... -1.10325546  0.60439732
  -0.10558415]
 ...
 [ 0.3429808  0.00330087  0.14964075 ... -0.73518964 -0.68519336
  -0.27575966]
 [-0.84488505  0.1597866  -0.47073225 ... -0.24020459 -0.37110101
   1.17073215]
 [-0.84488505 -0.8730192  0.04624525 ... -0.20212881 -0.47378505
  -0.87137393]]
```

In [16]: `X = standardized_data`  
`Y = diabetes_dataset['Outcome']`

In [17]: `print(X)`  
`print(Y)`



```
[[ 0.63994726  0.84832379  0.14964075 ...  0.20401277  0.46849198
    1.4259954 ]
 [-0.84488505 -1.12339636 -0.16054575 ... -0.68442195 -0.36506078
   -0.19067191]
 [ 1.23388019  1.94372388 -0.26394125 ... -1.10325546  0.60439732
   -0.10558415]
 ...
 [ 0.3429808   0.00330087  0.14964075 ... -0.73518964 -0.68519336
   -0.27575966]
 [-0.84488505  0.1597866  -0.47073225 ... -0.24020459 -0.37110101
    1.17073215]
 [-0.84488505 -0.8730192   0.04624525 ... -0.20212881 -0.47378505
   -0.87137393]]
```

```
0      1
1      0
2      1
3      0
4      1
```

```
763    0
764    0
765    0
766    1
767    0
```

Name: Outcome, Length: 768, dtype: int64

Train Test Split

```
In [18]: X_train, X_test, Y_train, Y_test = train_test_split(X,Y, test_size = 0.2, stratify=Y, random_state=2)
```

```
In [19]: print(X.shape, X_train.shape, X_test.shape)
```

```
(768, 8) (614, 8) (154, 8)
```

Training the Model

```
In [20]: classifier = svm.SVC(kernel='linear')
```

```
In [21]: #training the support vector Machine Classifier
classifier.fit(X_train, Y_train)
```

```
Out[21]: SVC
SVC(kernel='linear')
```

Model Evaluation

Accuracy Score

```
In [22]: # accuracy score on the training data
X_train_prediction = classifier.predict(X_train)
training_data_accuracy = accuracy_score(X_train_prediction, Y_train)
```

```
In [23]: print('Accuracy score of the training data : ', training_data_accuracy)
```

```
Accuracy score of the training data :  0.7866449511400652
```

```
In [24]: # accuracy score on the test data
X_test_prediction = classifier.predict(X_test)
test_data_accuracy = accuracy_score(X_test_prediction, Y_test)
```

```
In [25]: print('Accuracy score of the test data : ', test_data_accuracy)
```

```
Accuracy score of the test data :  0.7727272727272727
```

Making a Predictive System

```
In [28]: input_data = (5,166,72,19,175,25.8,0.587,51)

# changing the input_data to numpy array
input_data_as_numpy_array = np.asarray(input_data)

# reshape the array as we are predicting for one instance
input_data_reshaped = input_data_as_numpy_array.reshape(1,-1)

# standardize the input data
std_data = scaler.transform(input_data_reshaped)
print(std_data)

prediction = classifier.predict(std_data)
print(prediction)
```

```

if (prediction[0] == 0):
    print('The person is not diabetic')
else:
    print('The person is diabetic')

```

```

[[ 0.3429808  1.41167241  0.14964075 -0.09637905  0.82661621 -0.78595734
  0.34768723  1.51108316]]
[1]
The person is diabetic

```

```

In [27]: import warnings
warnings.filterwarnings("ignore")

```

## Creating Visualizations

```

In [33]: import matplotlib.pyplot as plt
import seaborn as sns

```

```

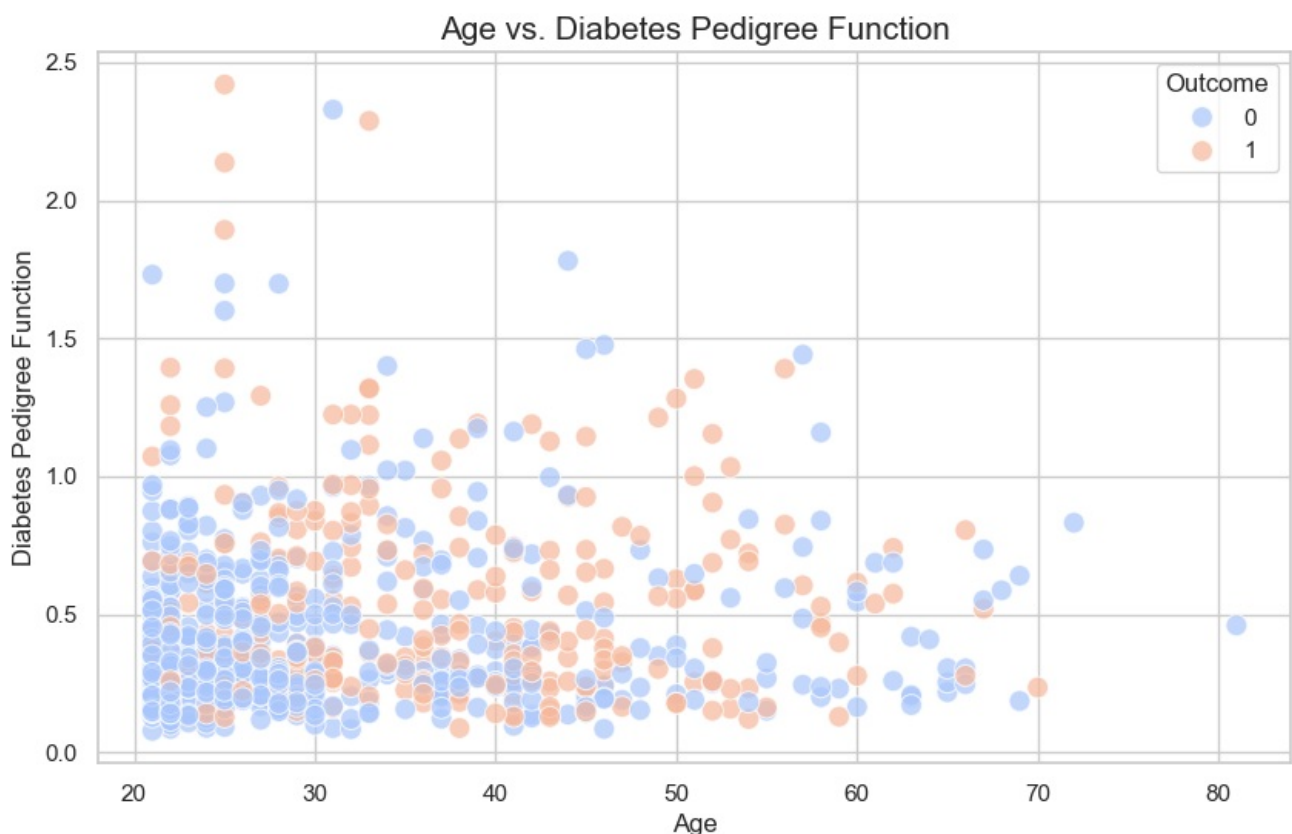
In [35]: # Set the style for the plot
sns.set_style("whitegrid")

# Create the scatter plot
plt.figure(figsize=(10,6)) # Optional: Adjust the figure size
scatter_plot = sns.scatterplot(
    x='Age',
    y='DiabetesPedigreeFunction',
    hue='Outcome',
    palette='coolwarm', # Customizes colors for 0 and 1
    data=diabetes_dataset,
    s=100, # Size of the points
    alpha=0.7 # Transparency for better visualization
)

# Add titles and labels
plt.title('Age vs. Diabetes Pedigree Function', fontsize=15)
plt.xlabel('Age', fontsize=12)
plt.ylabel('Diabetes Pedigree Function', fontsize=12)

# Show the legend and plot
plt.legend(title='Outcome', loc='upper right')
plt.show()

```



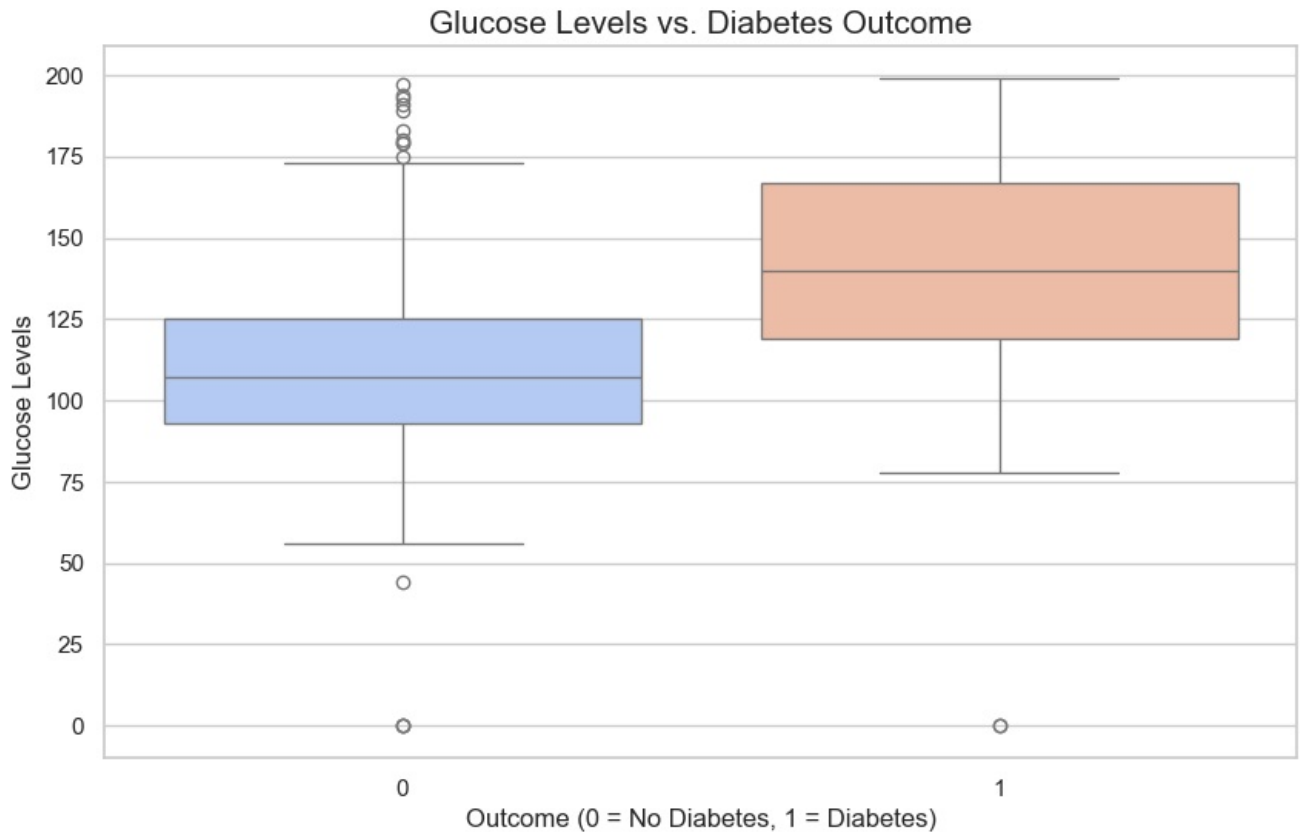
INTERPRETATION The above plot showed that there are more non-diabetic patients for people lower than 30 years of age, however it was observed from the Diabetes Pedigree Function that a person is likely to be diabetic if there is a family history of diabetes. It was also observed from the plot that persons within 30 to 50 years of age are at a higher risk of having diabetes. Something very worthy of note from the plot is that it is very rare(though not impossible) for a geriatric who has a history of diabetes to be non-diabetic.

```
In [36]: # Set the style for the plot
sns.set_style("whitegrid")

# Create the box plot
plt.figure(figsize=(10, 6)) # Adjust the figure size
box_plot = sns.boxplot(
    x='Outcome', # Outcome on the x-axis (0 or 1)
    y='Glucose', # Glucose levels on the y-axis
    data=diabetes_dataset, # Your dataset
    palette='coolwarm' # Color palette to differentiate between 0 and 1
)

# Add titles and labels
plt.title('Glucose Levels vs. Diabetes Outcome', fontsize=15)
plt.xlabel('Outcome (0 = No Diabetes, 1 = Diabetes)', fontsize=12)
plt.ylabel('Glucose Levels', fontsize=12)

# Show the plot
plt.show()
```



INTEPRETATION The above box plot is used to check how glucose levels are correlated with the disease condition. It can be clearly seen that non-diabetic patients have comparatively lower levels of glucose than the diabetic patients, so measures taken to reduce glucose levels could play a significant role in preventing diabetes.

## CONCLUSION

In this study, we explored key features of the dataset related to diabetes prediction, focusing on the relationship between glucose levels, age, family history (Diabetes Pedigree Function), and the outcome of diabetes diagnosis. The visualizations provided insights into the distribution of glucose levels across diabetic and non-diabetic patients, highlighting a clear distinction in glucose levels between the two groups. These insights reinforce the importance of glucose levels and genetic factors in diabetes prediction, supporting the validity of the SVM model used in this study for accurate classification.